A multidimensional model of academic self-efficacy

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ABSTRACT
The lockdown restrictions during the pandemic favored an intense use of online educational platforms thus bringing in front usability and technology acceptance. However, many studies are neglecting factors related to users, context, and actual use. Self-efficacy is an important variable explaining the behavior influencing the key determinants of technology acceptance and actual use. The purpose of this work is to develop and test a multidimensional model of academic self-efficacy that manifests in four dimensions: self-efficacy with self-regulated learning, computer self-efficacy, social self-efficacy, and self-efficacy with the course. The results show that although the four-factor structure is well supported, the factor loading on the computer self-efficacy is small.

Keywords
Academic self-efficacy, self-efficacy with self-regulated learning, social self-efficacy, computer self-efficacy.

ACM Classification
D.2.2: Design tools and techniques. H5.2 User Interface.

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INTRODUCTION
The lockdown restrictions during the pandemic favored an intense use of online educational platforms in universities. Students and teachers had to adapt to a new learning and teaching style, get new abilities, and develop self-efficacy in using the platform. Under these conditions, educational technology usability and acceptance became critical issues.

Technology acceptance depends on several key beliefs that influence the attitude toward using the system and consequently, the behavioral intention to use it [1, 12]. Most of the technology acceptance models (TAM) feature perceived ease of use and perceived usefulness as the main drivers of the behavioral intention to use.

Several studies analyzed the technology acceptance in relation to various aspects related to usability, quality in use, and user experience [19, 20, 24, 32, 33, 34, 41]. In a broader sense, usability is quality in use [6] and suggests focusing on effectiveness, efficacy, and satisfaction.

In a recent study, Bettayeb et al. [5] found that motivation, self-efficacy, usefulness, and usability are the main factors influencing the effectiveness of mobile learning.

Self-efficacy refers to the perceived capability of successful completion of a task [3]. As several studies pointed out, self-efficacy is an important variable explaining the behavior and having an influence on the key determinants of technology acceptance and actual use [11, 36, 39, 41].

Self-efficacy is multifaceted and related to a specific context of use [4]. Several scales have been developed that aim at measuring self-efficacy [9]. One approach is to develop a general scale with many items like GASE – the General Academic Self-Efficacy Scale, a 23-item scale [7]. This scale gives an overall score but is difficult to include it in other models. Another approach is to develop a multidimensional scale [4, 14] which enables the further use of dimensions as independent constructs in various models.

As Martin & March [28] pointed out, self-efficacy is an adaptive dimension of students' motivation and engagement. Taking a multidimensional perspective on self-efficacy enables a better understanding of the relationship between different facets and other variables related to the use of educational technology, such as usability, usefulness, and user experience.

The purpose of this work is to develop and test a multidimensional model of academic self-efficacy. The model manifests in four dimensions: self-efficacy with self-regulated learning, computer self-efficacy, social self-efficacy, and self-efficacy with the course. The analysis has been done on a sample of 326 Romanian university students.

The rest of the paper is organized as follows. In section 2, related work is discussed with a focus on the coronavirus crisis in education and learning motivation. The method and sample are presented in section 3. Then, the model estimation results are presented and discussed. The paper ends with a conclusion in section 5.

RELATED WORK
Self-efficacy refers to the judgment about being able to perform the task rather than to the actual performance. Self-efficacy is multidimensional and should be measured in the context of a particular domain [3, 4].

For Bandura [3] perceived academic self-efficacy has effects at the level of cognitive, motivational, affective, and selection processes, influencing students' school performance. Students' beliefs about their effectiveness in self-regulating learning and academic activities determine their aspirations, level of motivation, perseverance in the face of difficulties, and success in activities.

In another study, Bandura [2] states that the level of perceived self-efficacy correlates with the degree of difficulty of the goals that people set and influences their commitment to them. Also, people's beliefs in their efficacy determine the type of anticipatory scenarios they construct for themselves: those with a high level of self-efficacy visualize successful scenarios, while those with a low level of self-efficacy visualize failure scenarios [3].

In a study by Liu et al. [25], but also other similar studies cited by them, it is shown that there are significant negative correlations between academic self-efficacy and academic procrastination.

Martin and Marsh distinguished between adaptive and maladaptive dimensions of student motivation and engagement [28]. Adaptive dimensions are self-efficacy, mastery orientation, persistence, planning, valuing of school, and study management. Their study found five factors that predict academic resilience: self-efficacy, control, planning, low anxiety, and persistence (commitment).

The study of Yi and Hwang [41] extended TAM with three external variables: self-efficacy, enjoyment, and learning goal orientation which proved to be important predictors of the actual use.

Filipou [14] analyzed the academic self-efficacy in master's degree programs in Finnish universities by focusing on two dimensions: social self-efficacy and self-efficacy with the course. Her study found significant differences by field of study as regards social self-efficacy, which has been higher perceived by humanities students than by business and IT students.

The study of Jan [23] analyzed the relationship between prior experience, academic self-efficacy, computer self-efficacy, and satisfaction with online learning. The findings show that academic self-efficacy was the main predictor of satisfaction, female students had a higher perception of academic self-efficacy than males and older students had a higher perception of computer self-efficacy than males.

Tran [37] explored the factors influencing students' satisfaction and effectiveness of online education during the pandemic. The findings show a significant moderating effect of academic self-efficacy on the relationship between satisfaction and online education effectiveness.

Cassidy [8], traced the relationship between academic self-efficacy and academic resilience; he concluded that academic self-efficacy is a significant predictor of academic resilience, and students with lower or higher self-efficacy approach academic adversity differently. Its results are consistent with other previous studies [18, 28].

Mun & Hwang [31] proposed an acceptance model that includes learning goal orientation and application-specific self-efficacy. Their results highlighted the role of self-efficacy, enjoyment, and learning goal orientation in the adoption and actual use of the system.

METHOD

Research model and measures

Academic self-efficacy has been conceptualized as a second-order factor that manifests in four dimensions (first-order constructs): self-efficacy with self-regulated learning, self-efficacy with the course, social self-efficacy, and computer self-efficacy. The research model is presented in Figure 1.

The conceptualization as a multidimensional model enables analysis on two levels (global factor and each dimension) and the distinction between the contribution of each dimension to the global factor.

Self-efficacy with self-regulated learning (SEA) refers to the perceived capability of organizing and keeping up with academic work [3, 41].

Figure 1. The research model

Self-efficacy with the course (SEC) refers to course performance [14]. In this model, SEC refers to the perceived capability of understanding course literature and taking notes in class.

Social self-efficacy (SSE) refers to social learning aspects, such as talking with teachers and students or participating in debates [14, 16]. In this model, SSE refers to the perceived capability of asking questions, talking with teachers, and participating in class discussions.

Computer self-efficacy (CSE) refers to the perceived capability of learning how to use the learning platform and using it with minimal help [11].

Self-efficacy measures have been adapted from existing scales in the literature [4, 7, 11, 14, 16, 28]. The measures are presented in Table 1.

Table 1. Variables

SEA1	How well can you finish homework assignments by deadlines?
SEA2	How well can you organize your schoolwork?
SEA3	How well can you concentrate on school subjects?
SEC1	How well can you understand course literature?
SEC2	How well can you write essay papers and assignments?
SEC3	How well can you take notes of class instruction?
SSE1	How well can you participate in class discussions?
SSE2	How well can you ask a question in class?
SSE3	How well can you talk with professors?
CSE1	I can use a learning platform even if there is no one to teach me
CSE2	I can use a learning platform with minimal help
CSE3	I can learn how to use a learning platform on my own

Data analysis and procedures

The empirical validation of the multidimensional model follows a two-step approach based on the recommendations from the literature [13, 22, 27]: testing the inter-correlated first-order factor model and then the second-order factor model.

Confirmatory Factor Analysis (CFA) using the Structural Equation Modelling (SEM) approach was carried out to validate the models. The target (T) coefficient higher has been computed which indicates the existence of a second-order factor construct [27].

The convergent validity of the four-factor model has been evaluated based on the cut-off values for the composite reliability (CR) and average variance extracted (AVE), according to the recommendations from the literature [17]. The discriminant validity has been evaluated by comparing the square root of AVE with the correlations between constructs [15].

Based on the recommendations from the literature [17, 21], the following goodness-of-fit measures were used to assess the structural model: chi-square (χ^2), normed chi-square (χ^2/df), comparative fit index (CFI), non-normed fit index (NNFI), goodness-of-fit index (GFI), standardized root mean square residual (SRMR), and root mean square error of approximation (RMSEA).

An invariance analysis was carried out following the procedure described by Milfont and Fischer [30] before comparing the mean values for two dimensions: social self-efficacy and computer self-efficacy.

The model was analyzed with Lisrel 9.3 for Windows [29], using the maximum likelihood estimation method.

EMPIRICAL STUDY

Sample

The evaluation instrument has been administrated in 2023 to university students enrolled at Valahia University. After answering some general questions such as demographics (age, gender) and enrollment (faculty, year of study), students were asked to evaluate items on a 5-point Likert scale.

A total of 326 questionnaires have been received (97 males and 229 females). As regards age, 219 (67%) were under 30, 66 were between 30 and 39 (20%), and 41 were over 40 years old (13%). As regards the year of study, 202 (62%) were in the first year, 47(14%) in the second, and the rest (24%) in the third year of study.

Model estimation results

The descriptive statistics and factor loadings for the four-factors intercorrelated model are presented in Table 2.

Table 2. Descriptives and factor loadings (N=326)

Item	Mean	SD	Loading
SEA1	3.80	1.04	0.69
SEA2	3.77	0.97	0.90
SEA3	3.81	0.88	0.68
SEC1	3.86	0.87	0.75
SEC2	3.87	0.85	0.72
SEC3	3.85	1.03	0.66
SSE1	3.63	1.05	0.69
SSE2	3.71	1.08	0.83
SSE3	4.00	0.95	0.84
CSE1	4.06	0.99	0.82
CSE2	4.17	0.95	0.68
CSE3	4.00	1.05	0.84

All means are over the neutral value of 3.00 showing a good perception of the self-efficacy dimensions. The highest mean values have been reported for computer self-efficacy.

Factor loadings are over the threshold of 0.6 thus proving the unidimensionality of first-order factors. The model validation and estimation results are presented in Table 3 and Figure 2.

As shown in Table 3, the composite reliability (CR) of each first-order factor ranges between 0.754 and 0.831, above the minimum level of 0.70. The average variance extracted (AVE) is ranging from 0.506 to 0.624, above the cut-off value of 0.50. The results suggest a strong relationship between each dimension and its indicators.

Table 3. Convergent and discriminant validity (N=326)

	CR	AVE	SEA	SEC	SSE	CSE
SEA	0.805	0.583	**0.763**			
SEC	0.754	0.506	0.654	**0.711**		
SSE	0.831	0.624	0.513	0.655	**0.790**	
CSE	0.825	0.613	0.341	0.412	0.325	**0.783**

Discriminant validity has been assessed with the squared correlation test, by comparing the square root of AVE (in bold on the diagonal) with the correlations between constructs. Since the square root of AVE is higher than the correlations between constructs the model has adequate discriminant validity.

The goodness of fit indices (GOF) indicates a good level of fit of the model with the data: χ^2=115.85, DF=48, p=0.000, χ^2/DF=2.41, RMSEA=0.066, CFI=0.958, NNFI=0.943, GFI=0.946, SRMR= 0.0526.

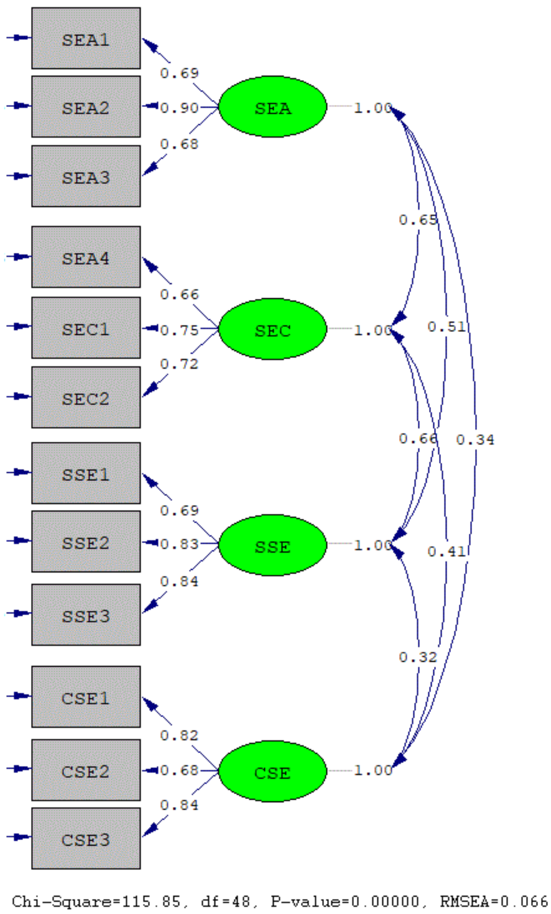

Figure 2. Four-factors intercorrelated - estimation results

The model estimation results for the second-order model are presented in Figure 3. With one exception (CSE), all factor loadings are over 0.6. The convergent validity of the model is very good since CR=0.804 and AVE=0.519, both over the cut-off values, which suggests that the first-order factors are sufficiently representative of the second-order factor and more than 50% of the variance in the first-order factors is shared with the global factor.

The goodness of fit indices (GOF) indicates a good level of fit of the model with the data: χ^2=115.96, DF=50, p=0.000, χ^2/DF=2.32, RMSEA=0.064, CFI=0.960, NNFI=0.947, GFI=0.946, SRMR= 0.0530.

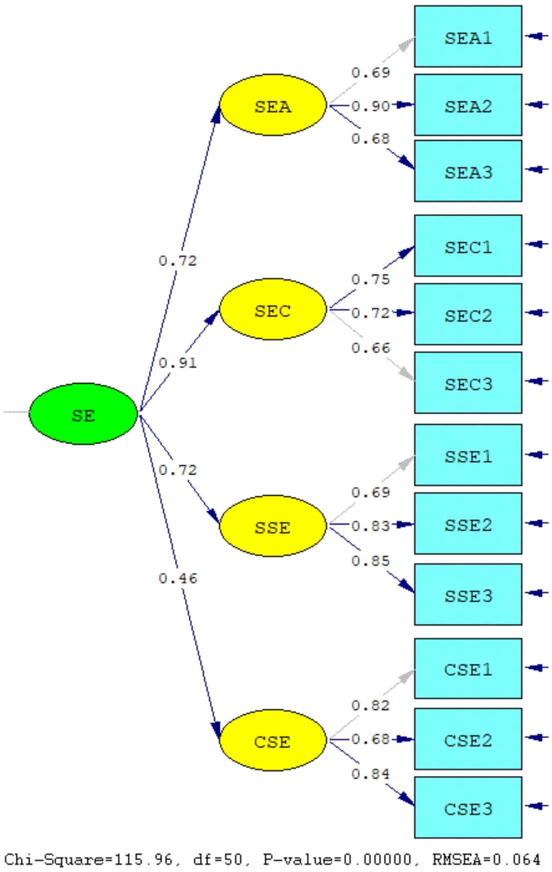

Figure 3. Global factor - estimation results

The calculated target coefficient between the first-order model and second-order model is 0.99 showing that the global factor explains 99% of the covariance among first-order factors. Based on these results, we may conclude that the second-order factor structure is well supported.

Overall, the model explains a 51.9% variance in self-efficacy with self-regulated learning, 82.7% in self-efficacy with the course, 51.5% in social self-efficacy, and 21.0% in computer self-efficacy.

Gender analysis

Before analyzing gender differences an invariance analysis is needed to check if both groups are interpreting the variables in the same way [38]. Multi-group confirmatory analysis is based on testing a hierarchical series of nested models, starting with an unconstraint model that fits all the samples together.

The nested models are obtained by adding constraints for invariance. Two tests have been used: nonsignificant $\Delta\chi^2$ and ΔCFI less than 0.01 [10, 38]. In the first step, the model has been tested on each sample. The results showed a good fit of the model with the data.

Then, a series of three models have been tested using the multigroup CFA: the unconstrained model for configural invariance, the model with constraints on factor loadings for metric invariance, and the model with constraints on intercepts for scalar invariance.

The invariance analysis testing results are presented in Table 4. The model fit is good in all cases. As it could be noticed, although the χ^2 differences are significant, the depreciation of CFI is below the cut-off value of 0.01 so the model has configural, metric, and scalar invariance, thus enabling the comparison of observed and latent means.

Table 4. Results of invariance analysis (N=326)

Model	χ^2	DF	CFI	ΔCFI	ΔDF	$\Delta\chi^2$	p
unconstraint	179.4	96	0.971				
Metric invar.	205.9	108	0.965	-0.006	12	26.52	0.009
Scalar invar.	217.0	112	0.963	-0.002	4	11.11	0.025

The mean differences are presented in Table 5. A one-way ANOVA (1, 324, 325) showed that differences are significant for the items SEA1 (F=7.087, p=0.008), SEA2 (F=4.556, p=0.034), and marginally significant for SEC3 (F=2.920, p=0.088).

Table 5. Differences in observed scores (N=97/229)

Item	Male		Female		Difference
	Mean	SD	Mean	SD	
SEA1	3.57	1.05	3.90	1.02	-0.33
SEA2	3.60	0.92	3.85	0.98	-0.25
SEA3	3.73	0.85	3.84	0.89	-0.11
SEC1	3.95	0.74	3.83	0.93	0.12
SEC2	3.86	0.92	3.87	0.82	-0.01
SEC3	3.70	1.05	3.91	1.01	-0.21
SSE1	3.68	1.02	3.61	1.07	0.07
SSE2	3.81	1.05	3.66	1.09	0.15
SSE3	4.02	0.94	4.00	0.96	0.02
CSE1	4.02	1.08	4.08	0.96	-0.06
CSE2	4.04	1.04	4.22	0.91	-0.18
CSE3	3.97	1.09	4.01	1.03	-0.04

The gender differences at the dimension and global factor (SE) level are presented in Table 6. A one-way ANOVA (1, 324, 325) showed that differences are significant only for SEA (F=5.650, p=0.018).

Table 6. Differences at dimension level (N=97/229)

	SEA	SEC	SSE	CSE	SE
Male	3.63	3.84	3.84	4.01	3.83
Female	3.86	3.87	3.76	4.10	3.90
Difference	-0.23	-0.03	0.08	-0.09	-0.07

The mean values are higher for female students at the global factor level and three of the four dimensions.

DISCUSSION

The main contribution of this study is a theoretically grounded and empirically validated model featuring a second-order factor of academic self-efficacy with four dimensions. On the second level, academic self-efficacy was measured on four dimensions: self-efficacy with self-regulated learning, self-efficacy with the course, social self-efficacy, and computer self-efficacy.

The estimation results for the second-order factor show a very high factor-loading on the self-efficacy with self-regulated learning and a relatively low factor-loading on the computer self-efficacy.

The latter finding and the high mean values of the items suggest that computer self-efficacy is no longer a problem for university students and the factor is not so representative of academic self-efficacy. This suggests that for technology acceptance models, computer self-efficacy may not bring much value; rather, self-efficacy with the course and social self-efficacy could be more useful antecedents. This is consistent with the results of other studies that found the non-significant influence of the perceived ease of use on perceived usefulness and technology acceptance [26, 35].

The results have several educational implications: teachers need to understand the various facets of academic self-efficacy in order to better design the courses and focus on methods that stimulate students' self-efficacy.

The model has also practical implications for researchers aiming at better understanding the various factors that are influencing the acceptance, actual use, and effectiveness of an educational technology.

This is an exploratory study so it has inherent limitations. First, the sample of the research is not representative since it includes students from only one university so the results cannot be generalized at the national level. Second, several items have been eliminated and one first-order factor is measured with only one item.

CONCLUSION AND FUTURE WORK

Understanding the factors that have an impact on students' self-efficacy in online learning leads to better decisions on the design and delivery of online courses.

For the students of the pedagogical training programs and future teachers, academic self-efficacy is an indispensable factor both for their training and for their future profession. By understanding the role, the valences, and the influences that a high level of self-efficacy has on the academic performance of students, the future teacher can adopt a positive and proactive attitude, turning it into an objective of his activity.

This study contributes to a better understanding of the academic self-efficacy dimensions which, in turn, enables the development of models of technology acceptance and student satisfaction with a higher explanatory power.

Future research refine the scale and focus on the inclusion of the academic self-efficacy dimensions into larger models.

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