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THE EFFECTS OF A NEW E-TIVITY ON STUDENTS' PERFORMANCE AND SATISFACTION IN AN ONLINE COURSE

Carlo Cavicchia

Econometric Institute, Erasmus University Rotterdam, Rotterdam, The Netherlands.

Pasquale Sarnacchiaro

Department of Economics Management and Institution, University of Naples Federico II, Naples, Italy.

Abstract. *Online education is nowadays becoming increasingly important in students' learning process. To plan future activities within an online course, it is crucial to understand which factors mostly contribute to Student Satisfaction which, in turn, affects the students' performances. The data collected from students attending the course in Statistics of the bachelor's in Economics in Unitelma Sapienza was considered, with the aim to detect both what students appreciated the most about a specific interactive online activity (e-tivity) and what critical aspects they believed emerged from the experience. Moreover, the performances obtained by the students who took part in this e-tivity were compared with the ones of whom had not attended. Finally, the paper presents an aggregated index for the Student Satisfaction highlighting the main aspects of it.*

Keywords: *Online Higher Education, Composite Indicator, Statistics Course, Interactive Learning, Autonomous Learning*

1. INTRODUCTION

Even before the COVID-19 pandemic, online education was gaining popularity and its growth was already steadily on the rise. A year after the pandemic started, it appears that the education system is undergoing a thorough makeover, where online learning can be considered at the core of this radical transformation and is increasingly being considered as the "new normal" (Ritella and Sansone, 2020). All around the world, educational institutions are looking toward online learning platforms to continue with the process of educating students. E-learning is now applicable not only to students within academic courses, but it also extends to

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Email: cavicchia@ese.eur.nl
Email: sarnacch@unina.it

learning extracurricular activities. However, as with most teaching methods, online learning does also have its own set of pros and cons.

Among the positive aspects of this mode of learning there are: efficiency (Estelami, 2016), affordability, the accessibility of time and place, the improvement of student attendance and the flexibility in suiting different learning styles. Some of the negative aspects include the inability to focus on screens, technological issues, a general sense of isolation, the lecturers' need for training and the management of screen time. Moreover, with online learning students can get easily distracted by social media. Therefore, professors are required to keep their online classes engaging and interactive in order to help students staying focused throughout the lesson. In an online class, students might develop a sense of isolation and therefore professors tend to allow other forms of communication between students, peers, and lecturers.

In online universities, courses are based on pre-registered video-lessons (transmissive teaching model) and interactive activities (e-tivities) (Salmon, 2013). E-tivities aim to enlarge the participants' knowledge and expertise through structured actions directed towards the production of specific outcomes (i.e., an essay, solutions of exercises). E-tivities stimulate active participation and the interaction between (and within) learners and teachers, tutors, and experts (Pavey and Garland, 2004).

Focusing on the context of the three-year online degree course in Economics provided by Unitelma Sapienza (Academic Year 2019-2020), the goal of the present research is that of evaluating the impact that the introduction of a new e-tivity had on student learning and involvement.

In particular, in order to assess the potential improvements of this new e-tivity, students' performances were measured before and after the introduction of such e-tivity. The collection of data was accompanied by a study that aimed at exploring students' perceptions and appreciation of the e-tivity.

2. THE STUDY

This study was carried out within the context of the three-year online degree course in Economics provided by Unitelma Sapienza (Academic Year 2019-2020). Particularly, the research used as its case study the course in Statistics, which was based on a e-learning model able to meet the learning needs and participation of students. This course's e-learning model was based on two pillars: pre-registered video-lessons (transmissive teaching model) and interactive activities (e-tivities). In order to define the e-learning model, it is also crucial to take into consideration the context constraints, the disciplinary aspects and the method of evaluating learning.

The typical context constraints were considered, such as: 1. The fact that enrollment is open throughout the year with no time limit, which consequently makes it more difficult to identify time windows that facilitate the proposal of activities centered on interaction and collaboration; 2. The extremely variable number of students enrolled in courses; 3. The requirement for students to asynchronously use the didactic activities, which are complementary to the study of the standard materials; 4. The rewarding complementary didactic activities rather than the penalizing ones (Sansone and Cesareni, 2019).

The Statistics course was organized in three modules. Each module of the course was taught through a combination of fifteen to eighteen video lessons (transmissive teaching) and two web-conferences with a self-assessment test (interactive activities). Moreover, an e-tivity called "Statistics in practice" was included to stimulate interaction both among students and between students and lecturers.

In "Statistics in practice", the professor started by engaging the students in reading the case study or watching a video that summarized the case study and the dataset to be used. Students then worked either in small groups or individually to solve the case study and the professor set milestones defining what students should accomplish in order to help them manage their time. Seven days before the exam, students uploaded their case study solutions to the platform and each solution was then graded with a maximum score of 3 points, which contributed to the final grade required to pass the exam (summative evaluation), expressed in a scale which went up to thirty points. The e-learning model, called *Statistics*, balanced out transmissive teaching and interactive activities according to the following percentages: 73% for transmissive teaching and 27% for interactive activities.

In 2018-2019, 1002 students participated in the Statistics course; out of these, only 685 took the final exam, and 68% of the students passed the exam with an average grade of 22.4 out of 30. Considering the 685 students who took the exam, 35% followed the Statistics in Practice e-tivity. The results displayed in Table 1 show that the performance of those who did this e-tivity were better than those who did not participate in Statistics in Practice.

Given the better results of the students who participated in Statistics in

Tab. 1: Students' performance for model Statistics respect to the adhesion to the e-tivity Statistics in Practice

	Statistics in Practice	
	Yes	*No*
Enrolled Students	239	446
Exam passed	182 (76%)	259 (58%)
Average final grade	23.6	21.8

Practice, to improve performance and stimulate active learning it was decided to change the e-learning model by giving more importance to interactive activities (Sansone, 2020). The new set up for the e-learning model included twelve to fifteen video lessons (transmissive teaching) per Module and an e-tivity called StatUp (interactive activities), while Statistics in Practice completed the teaching program.

The ideas of e-tivities were based largely on participants "making sense" of material through interaction with their peers and with their e-moderators (lecturers and tutors) (Sansone et al, 2018).

StatUp resulted in a very articulated e-tivity which included the following activities, carried out according to the time sequence shown in Figure 1:

- Entry test on basic knowledge.
- A summary Webinar for each of the three Modules with summary maps included.
- An office hour meeting per Module where the professor answers the students' questions.
- A Test with formative evaluation at the end of each Module.

StatUp was a non-mandatory activity, which enrollment was made available thirty days before the exam.

The new teaching model called *Statistics-StatUp* balanced transmissive and

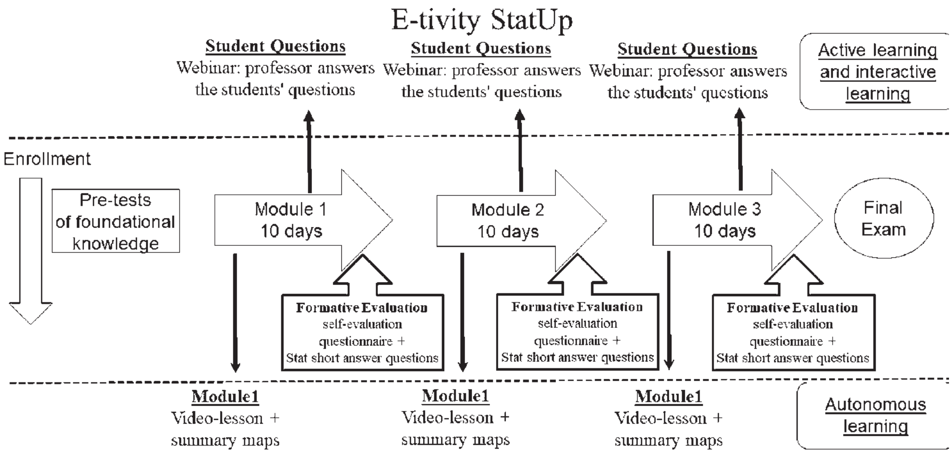

Fig. 1: StatUp Framework - The e-tivity StatUp is designed to be completed within one month

interactive teaching in a different way if compared to the first model, the percentages being 59% and 41%, respectively. Both the *Statistics* and *Statistics-StatUp* models are of the blended type (BeL - Blended e-Learning) and are proportionally modulated between transmissive teaching and interactive teaching. Specifically, a Student Questions activity was planned at the end of each module. This tool belongs within the vast set of ways to enhance the online classroom learning environment and to engage students. Currently, scholars are increasingly discussing about student-instructor interactions that take place daily in the online classroom; although students interact with each other and with the content, it is the student-instructor interaction and connection that appears to support the student's need to connect with the course content in a personal manner.

With the aim of evaluating the performances of the students after the introduction of the StatUp e-tivity, we considered the results of the May-July 2020 session. Among the 265 students enrolled, only 186 (just over 70%) attended the final exam. Only 60.7% of those who eventually attended passed the exam, which is less than those of the two-year period previously considered, where 68% of those who attended passed.

Before comparing the performances of the two groups of students, i.e., those who followed StatUp and those who did not, we checked the homogeneity of university performance before taking the Statistics exam, finding that the two groups resulted similar (Table 2).

However, the performances were profoundly different among those who

Tab. 2: Students' performance for model Statistics and Statistics-StatUp (2020)

	Statistics	Statistics-StatUp	Total
Number of exams passed (before Statistics)	14.4	13.5	13.9
Average Exams grade (before Statistics)	24.1/30	24.3/30	24.2/30
Attended	126	60	186
Passed	66 (52.4%)	50 (83.3%)	116 (60.7%)
Failed	60 (47.6%)	10 (16.7%)	70 (39.3%)
Average final grade	23/30	24/30	23.4

participated in StatUp (Table 2). In detail, it is interesting to note that the percentage of success for those who took part in StatUp was 83.3%, compared to the percentage of 52.4% for those who did not attend the e-tivity StatUp. Despite this difference being statistically significant (p-value 0,00001), it should be noted that when comparing the difference between the two respective averages for the final grades, the difference becomes not statistically significant (p-value 0,0908).

3. STUDENT SATISFACTION FOR THE E-TIVITY STATUP

After assessing the impact of the e-tivity StatUp on student learning, the study aimed at exploring students' satisfaction by using an anonymous questionnaire administered online via Google Forms at the end of the StatUp e-tivity. Through the semi-structured questionnaire, students were asked to evaluate, on a 5-point Likert scale (where 1= null, 2= poor, 3= sufficient, 4= fair, 5= excellent), the following characteristics of StatUp: Importance of Teaching materials, Clarity of Teaching materials, Teaching involvement, Lecturer Clarity, Learners Interactions, Intermediate verifications Tests, duration of the StatUp e-tivity, Course Technology and Student Satisfaction.

In the end, two open-ended questions were investigated: first, what students appreciated the most about the activity and, second, what critical aspects they believe emerged from the experience. The results in Table 3 show wide student satisfaction for all aspects of StatUp. In fact, almost all the characteristics show an average rating value higher than 4 on a scale of 5. The only two characteristics that show an average value being slightly lower than 4 were the *Duration of the activity* and the *Learners Interactions*. It should be noted that the students expressed a particular appreciation for the usability of the platform (*Course Technology*), followed by *Lecturer Clarity* and *Lecturer Involvement* as well as the Teaching material developed for the e-tivity.

Tab. 3: Students' perceptions on e-tivities: average on a 5-Points Likert Scale

Items	Mean	SD
Importance of Teaching materials	4.24	1.09
Clarity of Teaching materials	4.11	1.07
Teaching involvement	4.24	1.08
Lecturer Clarity	4.24	1.01
Learners Interactions	3.89	0.99
Intermediate verifications Tests	4.11	1.12
E-tivity StatUp duration	3.76	1.16
Course Technology	4.34	0.84
Student Satisfaction	4.32	0.98

4. A COMPOSITE INDICATOR FOR STUDENT SATISFACTION

In order to evaluate the study, the Second-Order Disjoint Exploratory Factor Analysis (2O-DFA, Cavicchia and Vichi, 2021a) model was considered, which consists of two nested factor models. Formally, let **x** be the (J × 1) multivariate random variable with mean vector μ_x and J-dimensional variance-covariance matrix $\boldsymbol{\Sigma}_x$. The following two simultaneous equations must therefore be considered:

$$\mathbf{x} - \boldsymbol{\mu}_x = \mathbf{A}\mathbf{y} + \boldsymbol{e}_x \quad (1)$$

$$\mathbf{y} = \mathbf{c}g + \mathbf{e}_y \quad (2)$$

where **A** is the (J × H) matrix of unknown specific factors loadings, **y** is the non-observable (H × 1) vector of unknown specific factors scores and $\mathbf{e}_x$ is a (J × 1) random vector of errors for the model (1). *g* **is** a non-observable random variable normally distributed with mean 0 and variance 1, **c** is the (H × 1) vector of unknown general factor loadings and $\mathbf{e}_y$ is a (J × 1) random vector of errors for the model (2).

The complete model might be written including equation (2) into equation (1) and considering the loading matrix **A** equal to the product **BV**, where **B** is a diagonal matrix and **V** a row stochastic and binary matrix. 2O-DFA for *n* multivariate observations is therefore defined as follows

$$\mathbf{X} = \mathbf{Y}\mathbf{V}'\mathbf{B} + \mathbf{E}_x = \mathbf{g}\mathbf{c}'\mathbf{V}'\mathbf{B} + \mathbf{E}_y\mathbf{V}'\mathbf{B} + \mathbf{E}_x \quad (3)$$

Under the assumption of normality for **Y**, $\mathbf{E}_x$ and $\mathbf{E}_y$, it can be easily derived that $\mathbf{X} \sim \mathbf{N}_J(\boldsymbol{\mu}_x, \boldsymbol{\Sigma}_x)$, with

$$\boldsymbol{\Sigma}_x = \mathbf{B}\mathbf{V}\boldsymbol{\Sigma}_y\mathbf{V}'\mathbf{B} + \boldsymbol{\Psi}_x \quad (4)$$

where $\boldsymbol{\Sigma}_x = \mathbf{c}\mathbf{c}' + \boldsymbol{\Psi}_y$ represents the correlation matrix of the specific factors, $\boldsymbol{\Psi}_x$ is the *J*-dimension diagonal positive definite variance-covariance matrix of the error of model (1) and $\boldsymbol{\Psi}_y$ is the *H*-dimension diagonal positive definite variance-covariance matrix of the error of model (2).

2O-DFA aims at reconstructing $\boldsymbol{\Sigma}_x$ and $\boldsymbol{\Sigma}_y$ in terms of 2J + H unknown free parameters in **B**, **V**, $\boldsymbol{\Psi}_x$, **c** and $\boldsymbol{\Psi}_y$. The discrepancy function to minimize with respect to **B**, **V**, $\boldsymbol{\Psi}_x$, **c** and $\boldsymbol{\Psi}_y$ is

$$D(\mathbf{x}_i, \mathbf{B}, \mathbf{V}, \mathbf{c}, \boldsymbol{\Psi}_x, \boldsymbol{\Psi}_y) = \log|\mathbf{B}\mathbf{V}(\mathbf{c}\mathbf{c}' + \boldsymbol{\Psi}_y)\mathbf{V}'\mathbf{B} + \boldsymbol{\Psi}_x| + \mathrm{tr}\{[\mathbf{B}\mathbf{V}(\mathbf{c}\mathbf{c}' + \boldsymbol{\Psi}_y)\mathbf{V}'\mathbf{B} + \boldsymbol{\Psi}_x]^{-1}\mathbf{S}\} \quad (5)$$

where $\mathbf{S} = \sum_{i=1}^{n}(\boldsymbol{x}_i - \overline{\boldsymbol{x}})(\boldsymbol{x}_i - \overline{\boldsymbol{x}})' / \boldsymbol{n}$ is the J-dimensional sample variance-covariance matrix and $\overline{\boldsymbol{x}}$ is the sample mean. With the aim of minimizing the discrepancy function, a descent coordinates algorithm was developed. This method was used to detect which factors have an impact on the Waste Management in EU (Cavicchia et al., 2021).

In order to formalise and analyse Student Satisfaction, we propose an aggregated index that best represents this latent concept via a hierarchical statistical method able to detect the main dimensions of the measured phenomenon. 2O-DFA thus identifies a system of loadings able to define a second-order hierarchy having the general construct on top. In detail, our study hypothesises a hierarchical model which aim is to represent the multidimensionality of Student Satisfaction and to define a Composite Indicator (CI, OECD, 2008). In order to better understand the aim of this work, it is worth recalling the definition of CI: a CI is formed when observed variables are compiled into a single index, based on an underlying model of the multi-dimensional concept that is being measured (OECD, 2004; Cavicchia and Vichi, 2021b). Disjoint sets of variables are used when defining the main dimensions (Specific CIs) of Student Satisfaction, representing the first order of the hierarchy, whereas the second order is represented by the Student Satisfaction index (General CI). Thus, it is noteworthy that the model involves the definition of dimensions, where each dimension is characterized by specific questionnaire items (i.e., questions). Furthermore, our approach takes into account the relations among the observed variables while considering the correlations among the specific latent constructs.2O-DFA is applied to the dataset composed by 9 observed variables (Importance of Teaching materials, Clarity of Teaching materials, Lecturer Involvement, Lecturer Clarity, Learner Interactions, Intermediate verification tests, E-tivity StatUp duration, Course Techology, Student Satisfaction), which are the columns of **X** in the formulation of the model. It is worth underscoring that since the study focuses on the construction of a CI for Student Satisfaction, the latter variable is purposedly discarded from the analysis so to avoid affecting the results. It is important to notice that the variable Student Satisfaction results to be inconsistent with the other variables, i.e., the correlations between Student Satisfaction and the other variables are always lower than 0.55 (Table 4), and the mean of the variables seems far from Student Satisfaction. This inconsistency suggests the use of a methodology that is able to assign different weights to the observed variables, as the “equal weight” approach results inappropriate and potentially misleading.

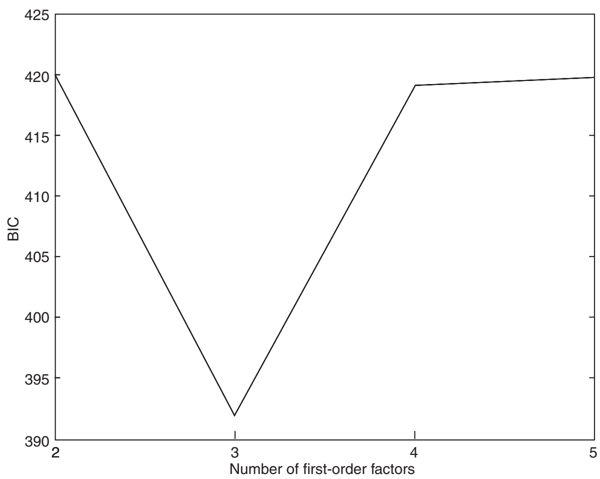

Fig. 2: Plot representation for the values of BIC for each number of first-order factors (*H*)

The main scope of our study is to detect the model that could properly measure Student Satisfaction based on the observed variables present in the dataset, with the goal of identifying the dimensions that reflect this multidimensional phenomenon. To do so, we first investigate whether all observed variables are concordant with each other and, consequently, if they can consistently measure a general latent concept. All relationships result positive and correctly inserted in the theoretical framework, such that, all variables reflect the associated latent dimension.

Tab. 4: Correlations between Student Satisfaction and the items

Items	Student Satisfaction
Importance of Teaching materials	0.54
Clarity of Teaching materials	0.49
Teaching involvement	0.42
Lecturer Clarity	0.47
Learners Interactions	0.35
Intermediate verifications Tests	0.54
E-tivity StatUp duration	0.41
Course Technology	0.28

The best model (i.e., the model with the optimal number of dimensions, H) is selected by the Bayesian Information Criterion (BIC, Schwarz, 1978), and results to be the one with 3 dimensions and related first-order factors (in detail BIC equals to 394.17, Figure 2). The model is consistently constructed because all dimensions result unidimensional and strongly reliable (Table 5), and, thus, as reported in Table 6, the general construct Student Satisfaction (i.e., **g** in the formulation of 2O-DFA) results well identified by the three dimensions (i.e., the columns of **Y** in 2O-DFA): Teaching Material (TM, characterized by Importance of Teaching materials, Clarity of Teaching materials), Teaching Involvement (TI, characterized by Lecturer Involvement, Lecturer Clarity) and Course Management (CM, characterized by Learner Interactions, Intermediate verification tests, E-tivity StatUp duration, Course Techology). Table 6 displays the first-order loadings contained in **A** in the formulation of 2O-DFA.

Tab. 5: Reliability and unidimensionality of dimensions. The values of Cronbach's Alpha (Cronbach, 1951) to measure the reliability and the value of second largest eigenvalue of the variance-covariance sub-matrices related to the subsets of variables to measure the unidimensionality are reported

Dimension	Cronbach's alpha	Unidimensionality
Teaching Material	0.80	0.76
Teaching Involvement	0.92	0.14
Teaching Involvement	0.92	0.14
Course Management	0.88	0.22

Furthermore, the model is able to explain the 67.34% of the variance and the goodness of fit equals to 0.88. In order to assess the variable selection and the goodness of the estimations, we present the standard errors for the estimation of first-order factor loadings). Specifically, the standard errors were calculated according to the formulas presented by Lawley and Maxwell (1971) for the one-factor case.

With the aim of testing the significance of factor loadings, we considered the Bonferroni correction which controls the family-wise Type I error. All the observed variables result statistically significant. It is therefore worth underlining that even if the loading of the item Learner Interactions results the lowest, the item results significant in the definition of the construct CM and it must be considered into the model. For assessing the reliability of the dimensions, we consider the widely used index Cronbach's Alpha (Cronbach, 1951). A credited rule of thumb for describing reliability was given by George and Mallery (2003) as follows: if the index is larger than 0.9 the level of reliability is excellent, when it lies within [0.8,0.9] the level is good, when the index is within [0.7,0.8[we can consider the level of reliability acceptable, and, finally, indices under 0.7 are unacceptable. For assessing unidimensionality, we used the second largest eigenvalue of the variance-covariance sub-matrix related to the subset of variables, which must be smaller than 1.

Tab. 6: Results of the optimal model for defining dimensions of Student Satisfaction

Items	TM	TI	CM	St. Err.
Importance of Teaching materials	0.927			0.01
Clarity of Teaching materials	0.927			0.01
Lecturer Involvement		0.884		0.01
Lecturer Clarity		0.884		0.01
Learner Interactions			0.441	0.01
Intermediate verification tests			0.728	0.03
E-tivity StatUp duration			0.885	0.05
Course Technology			0.774	0.03

The TI dimension is the most important in the definition of the Student Satisfaction (Figure 3), with loadings (i.e., second-order loading, entry of **c** in 2O-DFA) equal to 0.89. Therefore, the model underlines the crucial role of the lecturer into the online teaching. All dimensions are positively correlated (with correlation equal to 0.65 between CM and TM; 0.59 between TI and CM; 0.72 between TM and TI), thereby reflecting the same latent concept (i.e., the Student Satisfaction).

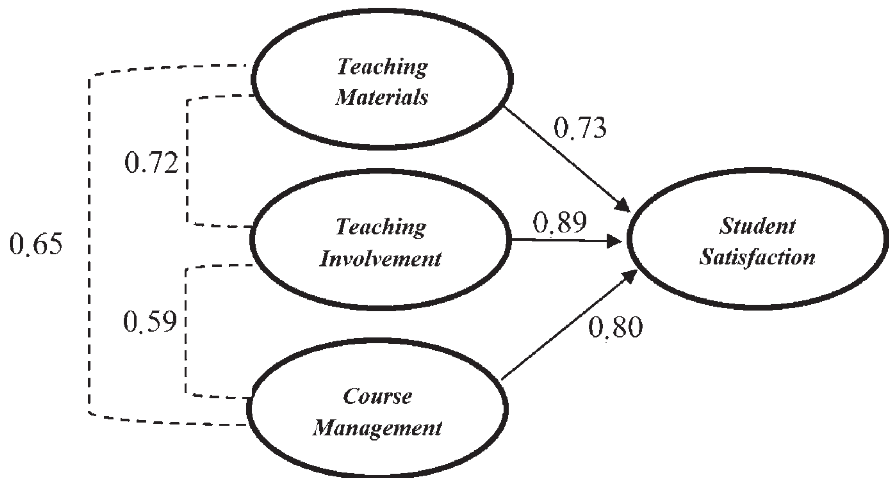

Fig. 3: Path diagram of the two-order hierarchy Student Satisfaction

In order to analyze the same model by gender we applied the multi-group procedure (Cavicchia and Sarnacchiaro, 2021). However, the difference in the second-order coefficient does not result statistically significant, which suggests rejecting the hypothesis to have two different models, one for men and one for women.

5. CONCLUSION

Our study considered the impact of a new e-tivity called StatUp, which was introduced in the Statistics course belonging to a three-year degree course in Economics at Unitelma Sapienza, where the e-tivity's impact was measured in terms of students' learning and satisfaction.

In the first case, we were able to verify that the students who took part in StatUp had a much better performance in terms of pass rate (effectiveness compared to the result) than those who had not enrolled in the e-tivity. However, this difference was not observed with regards to the average grade (effectiveness with respect to the quality of the result).

This leads to suggest the need for the implementation of an improvement action aimed at increasing the educational content within StatUp on the one hand, and the duration of the e-tivity itself on the other.

Subsequently, our study detected the students' satisfaction for the various aspects of StatUp, where a general satisfaction emerged. This result confirms what arose from other studies in relation to the importance of interactive teaching tools, especially in on-line courses. As scholar G. Salmon (2013) affirms: "[...] the key to active and interactive online teaching and learning lies in bringing us greater interaction and group participation".

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