A STUDY ON THE SATISFACTION WITH DISTANCE LEARNING OF UNIVERSITY STUDENTS WITH DISABILITIES: BIVARIATE REGRESSION ANALYSIS USING A MULTIPLE PERMUTATION TEST

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Abstract. *The Covid-19 pandemic led to considerable changes in instruction: all learning activities were switched to virtual mode, testing the adaptability of professors and students. Among the latter, a relevant effort was asked of individuals with disabilities, normally helped by technologies but forced to change some of their habits and methods. The paper takes into account data of an empirical survey administered in Ferrara (Italy). We carried out a bivariate regression analysis and applied a multiple permutation test in order to study the effect of personal factors and didactic critical issues on the perceived quality of distance learning. The original scientific contribution of the work is dual because it concerns both application and method. The good performance of the multiple permutation test was demonstrated by a Monte Carlo simulation study.*

Keywords: *Covid-19, Distance Learning, Disabilities, Student Satisfaction, Permutation Test*

1. INTRODUCTION

Since the Covid-19 pandemic began, academic teaching methods have changed substantially worldwide to ensure social distancing and contain the spread of infection. The introduction of distance learning has severely tested the adaptability of students who had to quickly learn to use new technological applications and tools, change how they attended lessons and adjust their study methods and approaches to exam preparation to the new context. The impact of distance learning was potentially even stronger for students with disabilities.

Since disabilities are an individual status related to environmental and personal conditions (Federici, 2007; WHO, 2001), nations must allow these individuals to exercise their human rights, removing obstacles resulting from disabilities (UN, 1948; UN, 1966; UN, 2006). For this purpose, when the Covid-19 emergency forced Italian institutions to turn distance learning into the norm for all students, schools and universities were recommended to take heed of individuals with disabilities (Italian PM, 2020).

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Since Italy was the first western country to face the Covid-19 pandemic, Italian Universities had to try innovative solutions in order to maintain educational continuity with the same standards of quality. In general, in the first months of the pandemic, instruction within the Italian academic system was mainly carried out through synchronous (live streamed) and asynchronous (video-taped) lessons. Health and safety concerns led to the suspension of all face-to-face activities, including practical ones such as internships, and redirected services for persons with disabilities virtually as well.

Although students may have missed physical settings and face-to-face activities, most of them progressively accepted the sudden switch to fully virtual learning (Giovannella, 2021). For persons with disabilities, a favorable approach to distance learning might be related to the increased sense of independence granted by the technology: learning and services reach their homes directly, overcoming mobility problems and making lessons available at any time (Dobransky et al., 2006).

Nevertheless, distance learning at both scholastic and university levels was widely criticized in the Italian literature and public debate. Online learning allegedly caused a regression to traditional and merely theoretical teaching methods because of the lack of direct communication with students (Capperucci, 2020). Another relevant remark concerned access to technological equipment: students lacked adequate technological means and internet connections. In addition, the transition to virtual lessons was also hampered by the technological problems faced by universities including their online transmission.

A serious approach to distance learning therefore requires that these problems not be neglected, especially with regard to persons with disabilities, whose social inclusion could be impeded by a fully virtual environment. In this context, being unable to access learning activities because of poor connections or equipment is likely to be seen as a form of disability in itself (Tănăsescu et al., 2010), impinging on social inclusion.

The inclusion of persons with disabilities in distance learning also depends on socio-psychological factors. Although some persons with disabilities may have more opportunities for social interaction in virtual rather than face-to-face environments (Kent, 2015), many of them could instead suffer from lacking interaction with their colleagues and professors and from difficulties in concentration.

This work concerns the analysis of satisfaction with distance learning in the Covid period, by disabled students who experienced both synchronous and asynchronous distance learning, in order to find whether the aforementioned aspects had an impact on their satisfaction and the extent of this impact. In particular, we deal with a case study that refers to the University of Ferrara (UNIFE), in Italy, in the second semester of the 2019/2020 academic year. During that period, instruction at the University of Ferrara included both synchronous and asynchronous lessons.

A random sample of students with disabilities was asked to provide information about their experience with both teaching methods and to indicate whether they suffered from a series of technological, organizational and socio-psychological problems stemming from distance learning. Seeing as, in our opinion, the distinction between the two types of online learning is important, we hypothesize that these issues have a greater impact on synchronous lessons, since asynchronous learning de facto weakens most of these problems. For instance, in asynchronous lessons, technological and organizational drawbacks are reduced, since students can attend video-taped lessons at any time, and the lack of concentration should be offset by the possibility to stop lessons and to watch them many times.

We also considered the impact on students' satisfaction with distance learning of some personal characteristics that represent typical confounding factors: gender, degree program, career status, and type of disability. Literature on this theme is extremely limited, considering that the topic is very recent.

This research aims at giving an original and innovative contribution to the debate on the education of persons with disabilities, with focus on distance learning in the Covid-19 period. Originality and innovation regard both the methodological and the applied points of view. An original dataset, based on a survey designed and carried out by the authors, is considered. The methodological innovation concerns the use of a bivariate regression model to investigate the perceived satisfaction of disabled students with distance learning by distinguishing synchronous and asynchronous learning as dependent variables. Moreover, an innovative contribution consists in the use of an advanced nonparametric statistical testing method applied to the bivariate regression model, to detect possible causes of the lack of inclusive education related to disabilities because of distance learning. Section 2 is dedicated to the description of the survey performed in Ferrara. In section 3, the innovative methodological approach is presented. Section 4 concerns a Monte Carlo simulation study to demonstrate the good performance of the proposed testing method. Section 5 includes results and discussion. Conclusions are in section 6.

2. THE CASE STUDY

The empirical survey was carried out on 3 June 2020. It must be premised that, unlike other nations, Italian legislation distinguishes specific learning disabilities (SLD), including dyslexia, dysgraphia, dysorthography and dyscalculia (Law n. 170/2010), from other disabilities (Law n. 295/1990 and Law n.104/1992), henceforth denoted by DIS. The target population of the survey consisted of 434 students enrolled in undergraduate and graduate programs suffering from SLD or DIS. They represent 1.73% of the student population enrolled at the University of Ferrara in the 2019/2020 academic year.

2.1 DATA AND METHODS

The survey involved a simple random sample of 87 students with disabilities enrolled at the University of Ferrara at the end of the second semester of the 2019/2020 academic year, i.e. the first semester of distance learning due to the covid-19 pandemic. The interview was carried out online, by setting up the questionnaire on a web form accessible to students via a link sent to them by email. We decided to select only 87 students (20% of the population size) due to the need to conduct the survey in a very short time and because this sample size guaranteed sufficient power of the test (see simulation study). In fact, the adopted nonparametric method is a valid solution for small sample sizes. The participation rate is 95.4% because 83 out of 87 students completed the survey.

These students experienced both synchronous teaching, or lessons carried out in live streaming, and asynchronous teaching, or videotaped lessons available and watched on the course web site. Students were asked to evaluate their distance learning experience in the mentioned semester, and they provided two evaluations: one for the synchronous lessons and one for the asynchronous lessons. The assessments consisted in numeric scores, ranging from 1 to 10. Therefore, we had a bivariate numeric response variable.

As shown in Table 1, the general satisfaction of students is evident in both teaching modes, because the positive evaluations (from 6 to 10) prevail over the negative ones. The sample indices of central tendency confirm this conclusion, because all their values are greater than 6. Satisfaction with live streaming seems to be less than that of videotaped lessons but the variability of the former assessments appears slightly greater than that of the latter. This is confirmed by the values of the sample measures of location and variability. Both distributions are skewed to the left but, due to the greater concentration of frequencies on the best scores, in the case of asynchronous teaching, the asymmetry of this distribution is higher. The evident diversity between the two distributions is confirmed by the fact that the former is platykurtic and the latter is leptokurtic (see Table 1).

These considerations on the marginal distributions of judgments suggest the advisability of adopting non-parametric methods. Indeed, the assumption that the data derive from normal or approximately normal populations seems implausible and distribution-free methods, that do not require the estimation of unknown parameters, seem more appropriate. As expected, the quality assessments of videotaped lessons tend to be better, probably because, as mentioned earlier, for disabled students, the chance to watch the videotaped lessons several times, focusing on some key or unclear concepts, is more important than the possibility to interact with the professor, also to compensate for learning deficiencies attributable to the student's disability.

Tab. 1: Descriptive statistics (sample indices) of the marginal distributions of the response variables (source: our elaborations on data from the 2020 University of Ferrara survey on disabled students)

Statistics	Evaluation of synchronous teaching	Evaluation of asynchronous teaching
Mean	6.373	7.675
Median	7.000	8.000
Mode	7.000	10.000
percentage □6	65.06%	81.93%
std.dev.	2.473	2.410
coef.var	38.8%	31.4%
Skewness	-0.546	-1.118
Kurtosis	2.791	3.517

Another reason for adopting nonparametric methods is related to the dependence between the two responses. The assumption of normality implies that of linear dependence. The sample Pearson's correlation index between the observed scores of the two responses is equal to 0.485, suggesting a positive moderate linear dependence. Thus, since the two response variables are not independent, a bivariate model is more appropriate than two separate univariate models. In fact, the bivariate model takes into account all the available information, including the dependence between the two responses. Hence, separate univariate regression analyses may lead to biased results.

Since normality seems implausible, linear correlation is not sufficient to represent the dependence structure between the two variables. The two variables may be strongly dependent even if not strongly linearly correlated. Thus, the dependence structure between satisfaction with synchronous teaching and satisfaction with asynchronous teaching is unknown and maybe nonlinear. Therefore, a bivariate nonparametric approach that does not need to model the bivariate distribution of the response and in particular the dependence between the two components such as the combined permutation test (Pesarin and Salmaso, 2010), seems suitable. In fact, this methodology takes dependence implicitly into account without strong assumptions about the family of bivariate distributions of the responses.

In order to investigate the effect of individual and academic factors on the satisfaction with distance learning among students with disabilities, a bivariate regression model is then used. For the reasons mentioned above, a multiple permutation test is carried out to test for the effectiveness of the model in explaining satisfaction with distance learning as a function of the various considered factors. The explanatory variables consist in dichotomous variables which represent either student characteristics or critical issues from the students' point of view that could affect the perceived quality of synchronous and asynchronous lessons.

2.2 HYPOTHESES

Students with disabilities (broadly, with health concerns) could reasonably be more concerned about classes going online than their peers without disabilities (Zhang et al., 2020). Students may deem advantageous the reduction of problems related to mobility, the greater convenience of attending multiple courses in a row in a virtual setting, the chance to attend videotaped lessons at any time and other resulting benefits. Regardless, this work focuses on the effect of individual characteristics and critical issues on the satisfaction for distance learning.

The survey considered three groups of problems potentially faced by surveyed students: socio-psychological, technological and organizational. Socio-psychological concerns mainly refer to low motivation and self-organization in attending online lessons on the one hand and to the lack of live communication with professors and colleagues on the other.

The sudden reduction of direct communication and immediate collaboration could indeed cause a lack of a sense of community, slowing down the process of learning because the emphasis of courses shifts to primarily theoretical content with a reduction of practical and applied components (Cojocariu et al., 2014; Song et al., 2004).

The lack of two-way interaction could, moreover, cause difficulties in concentration: research has shown that this phenomenon characterizes all kinds of students engaged in distance learning (Dhawan, 2020). Concentration disorders represent a serious matter for persons with disabilities who already suffer from these issues in daily life and must struggle even harder to "stay on task" in distance learning (Roberts et al., 2011; Re et al., 2014).

The current literature highlights other socio-psychological problems faced by persons with disabilities, such as fatigue and low mood (Denisova et al., 2020), but we only focused on the problems described above, considering them more related to distance learning (low mood could derive from other factors, such as anxiety stemming for the health emergency).

Technological problems refer to the poor quality of Internet connections and the lack of adequate technological tools and devices. These issues had a huge impact on Italian students' experiences with distance learning, since Internet connection infrastructures are not uniformly and effectively available throughout and across Italian provinces (Piras, 2020).

Organizational problems, instead, relate to poor planning of lectures, poor transmission quality, lacking availability of auxiliary services such as subtitles, inadequate communication by professors and offices, among others. In particular, audio/video transmission problems are relevant because they could preclude the possibility of dialogue and they could prejudice the academic career of people suffering from visual or hearing impairments (Roberts et al., 2011) and also from other disabilities (e.g. a bad audio transmission worsens attention deficits of persons with learning disabilities).

All the explanatory variables included in the model are dichotomous. Table 2 shows the list of independent variables, their definition, the frequency distribution, the mean value and the expected sign of the regression coefficients based on the possible effect of the predictors on the students' satisfaction. Among the individual characteristics, we consider gender, career status (whether they are freshman, or in the first year of academic studies, or not), course type and disability.

A dichotomy of degree programs is based on the different learning activities generally carried out: scientific courses have more practical activities, such as laboratories, and it could have been difficult to turn them into online lessons, since they require a deeper dialogue between lecturers and students (Biancalana, 2020).

Tab. 2. Dummy explanatory variables of the bivariate regression model

variable name	distribution		sample mean	coefficient expected sign
GENDER_M	1: male (33.7%)	0: female (66.3%)	0.337	?
COURSE_ELH	1: economic, legal or humanistic course (56.6%)	0: scientific or technical course (43.4%)	0.566	+
FRESHMAN	1: first year of academic career (43.4%)	0: otherwise (56.6%)	0.434	-
SLD	1: affected by Specific Learning Disability (84.3%)	0: other disability (15.7%)	0.843	-
DID_INTER	1: insufficient interaction with professors (12.0%)	0: no problem of interaction with professors (88.0%)	0.120	-
ORG_PBMS	1: organizational problems (38.6%)	0: no organizational problems (61.4%)	0.386	-
IT_PBMS	1: technological problems (38.6%)	0: no technological problems (61.4%)	0.386	-
CONC_DIF	1: concentration difficulty (49.4%)	0: no concentration difficulty (50.6%)	0.494	-
SOC_INT	1: missing social interaction with other students (48.2%)	0: no problem concerningsocial interaction (51.8%)	0.482	-

Students' satisfaction could moreover be affected by career status. Since the perceived ability to use study strategies and to process study material generally increases with training, a lower satisfaction is expected of freshmen, whose difficulties are worsened by the lack of academic experience (Costabile et al., 2013).

The type of disability could instead influence the ratings to our questionnaire if we consider learning disabilities independently: students with learning disabilities in the majority of cases suffer from impairments related to reading, so they need more time to learn what they read. The pressing times of synchronous learning could potentially reduce their productivity and, consequently, their satisfaction with that type of lesson.

Two course types are discretely defined: ELH (which includes Economics, Law and Humanistic studies) and BMT (Biomedical, Scientific and Technological courses). According to disability, the respondents are divided into the groups SLD and DIS. The possible problems related to distance learning considered in the model as factors are: insufficient didactic interaction, organizational problems, technological problems, concentration difficulty and lack of social interaction with other students. In general, each specific problem is observed more or less in four/five out of ten students with the exception of didactic interaction (only twelve percent). In the sample there is a prevalence of females, ELH courses, non-freshman and SLD (see Table 2). According to the above considerations and the consequent hypotheses on the direction of each predictor's effect, the expected sign of the estimates of the coefficients of the regression model is reported in the last column of Table 2.

3. THE BIVARIATE REGRESSION MODEL AND THE MULTIPLE PERMUTATION TEST

The regression model defined to represent the relationship between satisfaction with distance learning (jointly synchronous and asynchronous teaching), individual characteristics and didactic critical issues, is a bivariate model. Let random variable Y_{ij} denote the j-th dependent variable for the i-th statistical unit (student) and x_{iv} the value of the v-th predictor observed on the i-th statistical unit, with $j = 1,2,\ v = 1,2,\dots,k$ and $i = 1,2,\dots,n$, where k is the number of explanatory variables and n the sample size. The bivariate model consists of two equations, one for each dependent variable. The j-th equation is

$$Y_{ij} = \beta_{0j} + \beta_{1j}x_{i1} + \beta_{2j}x_{i2} + \cdots + \beta_{kj}x_{ik} + \varepsilon_{ij} \tag{1}$$

with stochastic error ε_{ij} such that $E[\varepsilon_{ij}] = 0, V[\varepsilon_{ij}] = E[\varepsilon_{ij}^2] = \sigma_j^2 = \sigma_{jj}$. Given that we want to apply a nonparametric approach, we do not assume normality or any other specific family of probability distribution for the error term of the model. The only condition is that the random vectors $(\varepsilon_{i1}, \varepsilon_{i2})'$, under the null hypothesis of no effect of the predictors on the responses are exchangeable with respect to the individuals. The covariance between ε_{i1} and ε_{i2}, denoted by σ_{12} may be not equal to 0. With respect to the classic model that assumes uncorrelation of errors on different statistical units, our model does not exclude the possibility of a correlation of errors on different individuals, due to exchangeability. Indeed, exchangeability is a weaker assumption than independence and implies higher flexibility and robustness of the method with respect to the departure from normality and/or other distributional assumptions of the parametric approach. Definitely, $E[\varepsilon_{ij}\varepsilon_{rs}] = \gamma_{js}$, with $i, r = 1,2,\cdots,n, i \neq r$, and it could be $\gamma_{js} \neq 0$. If $i = r$ then $\gamma_{js} = \sigma_{js}$. Parameters γ_{js} (covariances of errors referred to different individuals) and σ_{js} (variance/covariance of errors referred to the same individual) do not depend on i and r, hence these variances and covariances are the same for all individuals and all pairs of individuals.

The matrix representation of the model is the following:

$$\begin{pmatrix} Y_{11} & Y_{12} \\ Y_{21} & Y_{22} \\ \vdots & \vdots \\ Y_{n1} & Y_{n2} \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{pmatrix} \begin{pmatrix} \beta_{01} & \beta_{02} \\ \beta_{11} & \beta_{12} \\ \vdots & \vdots \\ \beta_{k1} & \beta_{k2} \end{pmatrix} + \begin{pmatrix} \varepsilon_{11} & \varepsilon_{12} \\ \varepsilon_{21} & \varepsilon_{22} \\ \vdots & \vdots \\ \varepsilon_{n1} & \varepsilon_{n2} \end{pmatrix} \quad (2)$$

which, in compact form, can be written as follows:

$$\underset{n \times 2}{\boldsymbol{Y}} = \underset{n \times (k+1)}{\boldsymbol{X}} \; \underset{(k+1) \times 2}{\boldsymbol{B}} + \underset{n \times 2}{\boldsymbol{E}}. \quad (3)$$

Point estimates of the coefficients can be determined following the least square approach. We are interested in testing the importance of the whole set of predictors, in other words in jointly testing all the regression coefficients. The null hypothesis is that none of the independent variables is useful for the prediction of the two dependent variables. Formally

$$H_0: \beta_{11} = \beta_{12} = \cdots = \beta_{k2} = 0. \quad (4)$$

The alternative hypothesis is the negation of the null hypothesis, that is at least one of the $2 \times k$ regression parameters is not equal to 0. Formally

$$H_1: \exists(j,v) \in \{1,2\} \times \{1,\cdots,k\}\ s.t. \beta_{vj} \neq 0. \tag{5}$$

Basically, the problem is a *MANOVA* of the bivariate regression model that, in the parametric framework, can be solved with the Pillai's test or a similar test.

According to the methodology of combined permutation tests (Pesarin and Salmaso, 2010), the problem can be broken down into $2 \times k$ partial tests, one for each coefficient. In other words, a multiple permutation test can be carried out, where the single testing problem is

$$H_{0,vj}: \beta_{vj} = 0 \ \text{ vs } \ H_{1,vj}: \beta_{vj} \neq 0 \tag{6}$$

and the overall problem can be represented as follows

$$H_0: \cap_{v=1}^{k} \cap_{j=1}^{2} H_{0,vj} \ \text{ vs } \ H_{1,}: \cup_{v=1}^{k} \cup_{j=1}^{2} H_{1,vj} \tag{7}$$

where the union/intersection symbols must be interpreted according to (4) and (5).

The proposed methodology consists in the application of a permutation test for each partial problem and in the combination of the p-values of the partial tests. The output of this combination is a combined test statistic that can be used for the final decision of either rejecting H_0 in favor of H_1 or not rejecting H_0. The dependence between the partial tests must be taken into account, in order to ensure a good performance of the test, in terms of probability of correct decision. This aspect is considered by determining the null permutation distribution of the partial tests through the permutation of the rows of the $\boldsymbol{X}$ matrix and keeping the rows of the $\boldsymbol{Y}$ matrix fixed. The random generation of quite a large number of permutations (at least 1000), according to the Glivenko-Cantelli theorem, provides a good approximation of the joint distribution of the partial test statistics and of the combined test statistic (Pesarin, 2001). This solution is preferable to that of the exact permutation test that considers all the $n!$ permutations, for computational reasons.

A reasonable choice for the test statistic, for testing $H_{0,vj}$ versus $H_{1,vj}$, is the absolute value of the least square estimator of the regression coefficient $T_{vj} = |\hat{\beta}_{vj}|$. Obviously, the partial null hypothesis is rejected for large values of the test statistic. Let $L_{vj}(t)$ be the significance level function for T_{vj} under the null hypothesis, that is $L_{vj}(t) = P\left[T_{vj} \geq t | H_0\right]$ and $l_{vj} = L_{vj}\left(t_{vj}\right)$, where t_{vj} denotes a given value taken by T_{vj} and the probability $P[A]$ is defined with respect to the permutation distribution, hence it is the proportion of permutations for which A is satisfied. A suitable combined test statistic is

$$T(t_{11}, t_{12}, \dots, t_{k2}) = \max_{v,j}\left(1 - l_{vj}\right) \tag{8}$$

and the p-value of the combined test is $P[T \geq T(|b_{11}|, |b_{12}|, \dots, |b_{k2}|)|H_0]$ where $b_{11}, b_{12}, \dots, b_{k2}$ represent the sample estimates of the regression coefficients and their absolute values are the observed values of the partial test statistics. The application of (8) is equivalent to use the so-called Tippett combining function (Bonnini et al, 2014).

The procedure of the multiple permutation test can be represented by the following steps:

1. Computation of the vector of observed values of the test statistics

$$\boldsymbol{t_{obs}} = (|b_{11}|, |b_{12}|, \dots, |b_{k2}|) = t(\boldsymbol{X})$$

2. B independent random permutations of the rows of the $\boldsymbol{X}$ matrix: $\boldsymbol{X_1^*}, \boldsymbol{X_2^*}, \cdots, \boldsymbol{X_B^*}$
3. Computation of the values of the test statistic for the B dataset permutations

$$\boldsymbol{t_b^*} = \left(\left|b_{11,b}^*\right|, \left|b_{12,b}^*\right|, \dots, \left|b_{k2,b}^*\right|\right) = t(\boldsymbol{X_b^*}), \text{ b=1,2,…,B}$$

4. Computation of the marginal significance level functions for the B dataset permutations

$$\boldsymbol{l_b^*} = \left(l_{11,b}^*, l_{12,b}^*, \dots, l_{k2,b}^*\right), \text{ b=1,2,…,B}$$

and of the observed dataset (marginal p-values)

$$\boldsymbol{l_0} = \left(l_{11,0}, l_{12,0}, \dots, l_{k2,0},\right)$$

where

$$l^*_{vj,b} = \left[\sum_{c=1}^{B} I_{\left[\,|b^*_{vj,b}|,\infty\right)} \left(|b^*_{vj,c}|\right) + 0.5 \right] / (B+1)$$

and

$$l_{vj,0} = \left[\sum_{c=1}^{B} I_{\left[\,|b_{vj}|,\infty\right)} \left(|b^*_{vj,c}|\right) + 0.5 \right] / (B+1)$$

with $I_A(\cdot)$ indicator function of the set A.

5. Computation of the value of the combined test statistic for each permutation and for the observed dataset

   $t^*_{comb,b} = \max_{v,j}\left(1 - l^*_{vj,b}\right)$ and $t_{comb,0} = \max_{v,j}\left(1 - l_{vj,0}\right)$

6. Computation of the p-value as

$$\left[\textstyle\sum_{b=1}^{B} I_{\left[\,t_{comb,0},\infty\right)} \left(t^*_{comb,b}\right) + 0.5 \right] / (B+1).$$

The software used for the statistical analyses is R. In order to implement the procedure of the multiple permutation test, for both application and simulation study, we created specific R scripts.

In real applications, together with the MANOVA for the validity of the whole model, interest is also focused on the effects of the single explanatory variables, to test the significance of the single coefficients. Following the logic of multiple testing, we can attribute the possible significance of the combined test to some specific partial tests, i.e. some specific coefficients, adjusting the p-values of the partial tests for controlling the Familywise Error Rate and avoiding that the probability of rejecting $\boldsymbol{H_0}$, when the null hypothesis is true, exceeds the significance level $\boldsymbol{\alpha}$ (Arboretti et al, 2012).

In our opinion, the application of the multiple permutation test with final adjustment of the partial p-values is preferable to the typical stepwise regression (e.g. backward elimination), because it considers the multivariate nature of the multiple test, composed by $2 \times 9 = 18$ partial components (partial test statistics) and thus it is more appropriate. In fact, it keeps into account the dependence between the single partial test statistics, jointly considering the whole set of explanatory variables and the two responses, instead of considering the marginal distribution over a subset of explanatory variables as typical of each phase of the stepwise regression.

4. SIMULATION STUDY

Since the work is also innovative from a methodological point of view, some results of a Monte Carlo simulation study are presented. The non-exclusively methodological nature of the work suggests that reporting some preliminary results in order to appreciate the power behavior of the proposed method. We postpone a deep study of the theoretical properties of the proposed permutation test to future research of a purely methodological nature.

In order to study the power behavior with respect to the sample size, 1000 datasets similar to the observed one, were simulated for different sample sizes ranging from 40 to 100. The multiple permutation test described above ($B = 1000$) was carried out. To simulate the dichotomous explanatory variables, the $v - th$ independent variable was assumed to follow a Bernoulli distribution with parameter θ_v ($v = 1,2,\dots,9$). The vector of θ parameters is

$$\boldsymbol{\theta} = (0.3, 0.6, 0.4, 0.8, 0.1, 0.4, 0.4, 0.5, 0.5)'$$

and, for each sample size n, 1000 $n \times 9$ matrices of explanatory variables were randomly generated from a 9-variate Bernoulli distribution with vector of parameters $\boldsymbol{\theta}$. For each simulated $\boldsymbol{X}$ matrix, a $n \times 2$ $\boldsymbol{E}$ matrix of values for the errors of the model was generated from the bivariate normal distribution $\mathcal{N}_2(\mathbf{0}, \boldsymbol{\Sigma})$ with

$$\boldsymbol{\Sigma}=\begin{pmatrix} 4.0 & 1.5 \\ 1.5 & 4.0 \end{pmatrix}$$

and the simulated $n \times 2$ $\boldsymbol{Y}$ matrix of values of the dependent variables obtained by computing $\boldsymbol{Y} = \boldsymbol{XB} + \boldsymbol{E}$. In order to make each response take integer values between 1 and 10, the data obtained are discretized by replacing any value greater than *10* by *10*. This data transformation determines the asymmetry of the two marginal distribution and makes such distributions non normal.

The 9×2 matrix of values of the coefficients, under the null hypothesis is

$$\boldsymbol{B} = \begin{pmatrix} 9 & 9 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{pmatrix}$$

and under the alternative hypothesis is

$$
\boldsymbol{B} = \begin{pmatrix} 9 & 9 \\ 0.0 & 0.3 \\ 0.1 & 0.1 \\ 0.3 & 0.5 \\ -1.2 & -0.9 \\ -1.8 & -0.6 \\ 0.0 & 0.6 \\ -0.8 & 0.2 \\ -2.3 & -1.5 \\ -0.1 & -0.9 \end{pmatrix}.
$$

The rejection rates of the permutation MANOVA under H_0 and H_1 as a function of the sample size *n* with *α=0.05*, are reported in Table 3. The test is approximated well, given that the estimated power is always less than the nominal α level 0.05 under H_0. The consistency of the test is proved by the increasing relationship between rejection rates and sample size. When the sample size is equal to 100, the test rejects the null hypothesis when the alternative is true with a probability almost equal to one. It is worth noting that a sample size equal to *80*, very similar to that of the present case study, corresponds to a power of *0.93*. Thus the simulation study proves that the test is powerful, unbiased, because the power under H_1 is higher than under H_0, and consistent, given that, when the alternative hypothesis is true, the power asymptotically tends to one.

Tab. 3: Rejection rates of the multiple permutation test (permutation MANOVA) under the null and alternative hypothesis (□= 0.05)

True hypothesis	**Samples size**			
	40	60	80	100
H_0	0.054	0.044	0.032	0.026
H_1	0.406	0.752	0.928	0.026

5. RESULTS AND DISCUSSION

The application of the permutation test described in section 3 to the data of the survey presented in section 2 provides the output shown in Table 4. The low values of the coefficients of determination indicate that the goodness of fit is not high. The proportion of variability of the dependent variables explained by the explanatory variables is moderate. However, the p-value of the combined permutation test is equal to 0.002. Therefore we have strong significance (p-value less than 0.01) and we can conclude that the whole set of explanatory variables affects the responses.

The partial p-values were adjusted with the Bonferroni-Holm method (Holm, 1979). Among the eighteen tested coefficients only that of CONC_DIF for the synchronous teaching has an adjusted p-value revealing significance. Specifically, the adjusted p-value of the test on the coefficient of the difficulty of concentration is 0.002, therefore we have a strong significance (p-value less than 0.01). The value of the coefficient's estimate is equal to -2.272. Hence, the mean satisfaction with the synchronous teaching of students who declared to have concentration difficulties, is less than the mean satisfaction of the other students and the difference is greater than 2. Instead, the effect of the concentration difficulty on the satisfaction for the asynchronous teaching is not significant. All the other adjusted partial p-values are large and far from significance. Hence, no other personal characteristic or didactic factor seems to affect either satisfaction with the live streaming or satisfaction with the videotaped lessons. Despite the presence of numerous dummy variables among the regressors, the problem of multicollinearity does not exist because all Variance Inflation Factors are well below the threshold of 5.

Definitely, the set of critical issues considered in this study seem to be irrelevant for the evaluation of both synchronous and asynchronous teaching. This may be one of the reasons why the R-squared takes moderate values. The only exception is represented by the difficulty of concentration, which represents an important element in determining the satisfaction of students with disabilities for synchronous teaching. This finding is consistent with the thesis that, for disabled students, the pros of distance learning outweigh the cons and that videotaped lessons are preferable to live streaming. This result is also consistent with the difficulty of concentration observed in all kinds of students engaged in distance learning (Dhawan, 2020) and with the daily lives of persons with disabilities, always suffering from these problems in the context of live lessons (Roberts et al., 2011; Re et al., 2014). The other critical issues, even though they were previously found as incisive in similar research (Denisova et al., 2020; Piras, 2020), proved to be more subjective than difficulty in concentration, so that they did not affect the satisfaction of the students of the University of Ferrara who participated in the questionnaire.

Personal factors taken into account, or gender, type of disability, type of course (from the point of view of disciplinary contents) and career status, are not relevant covariates in explaining satisfaction. Although scientific evidence highlights difficulties freshmen have in terms of their study strategy and methods (Costabile et al., 2013), this work indicates that this factor does not affect the satisfaction of disabled students. Also, potential problems related to the type of course were not relevant: practical activities in scientific courses were certainly held in an atypical way (Biancalana, 2020), but without a direct effect on students' satisfaction as compared with students of economic, legal or humanistic courses.

Tab. 4: Bivariate regression analysis and permutation tests on the model to predict disabled students' satisfaction with the distance learning at university (source: our elaborations on data from the 2020 University of Ferrara survey on disabled students)

	Evaluation of distance learning						
predictor	Synchronous teaching			Asynchronous teaching			VIF
	coef estimate	Pv	adj pv	coef estimate	Pv	adj pv	
GENDER_M	0.040	0.943	1.000	0.341	0.565	1.000	1.100
COURSE_ELH	0.053	0.929	1.000	0.118	0.843	1.000	1.200
FRESHMAN	0.304	0.607	1.000	0.484	0.408	1.000	1.200
SLD	-1.167	0.241	1.000	-0.935	0.340	1.000	1.100
DID_INTER	-1.781	0.011	0.170	-0.619	0.364	1.000	1.400
ORG_PBMS	-0.022	0.971	1.000	0.597	0.312	1.000	1.600
IT_PBMS	-0.754	0.197	1.000	0.212	0.710	1.000	1.200
CONC_DIF	**-2.272**	**0.000**	**0.002***	-1.540	0.009	0.146	1.800
SOC_INT	-0.104	0.898	1.000	-0.905	0.237	1.000	1.800
	Multiple R^2: 0.344	Adj R^2: 0.263		Multiple R^2: 0.209	Adj R^2: 0.112		
Overall permutation test on the whole model		0.002*					

*strong significance ($p < 0.01$); #moderate significance ($0.01 \leq p < 0.05$);
§weak significance ($0.05 \leq p < 0.10$)

The proposed non-parametric approach for testing the prediction validity of the model and the importance of the single explanatory variables, in our opinion, represents another important scientific contribution to deal with multivariate models, where the satisfaction for teaching approaches (or other services) is multidimensional and inferential parametric approaches are not suitable.

Finally, it is worth noting that surveys conducted on students with disabilities present specific difficulties that do not favor adequate sample sizes and high response rates, as demonstrated by the lack of scientific contributions on this topic in the literature. The adopted sampling method and the large response rate of this study ensure a high quality of the inferential results which represents another important added value of this work.

6. CONCLUSIONS

According to the existing literature, the statistical analysis of the data collected in the satisfaction survey of disabled students with distance learning, carried out by the University of Ferrara (UNIFE), represents one of the first contributions to the debate on factors and causes that determine the quality of teaching for students with disabilities during the covid-19 pandemic.

The bivariate regression analysis shows that the personal characteristics considered (gender, degree program, career status, type of disability) do not affect satisfaction, for both live streaming and videotaped lessons. For the critical issues taken into consideration, the conclusions are similar, indicating that the factors that have the greatest influence are probably others. Although these results could be considered unexpected and disappointing, we think that they reveal that the predictors of the perceived quality of distance learning for disabled students are different from those of other categories of students, which is an important finding of the study. The moderate goodness-of-fit of the model could depend on this. This can be considered a limitation of our study, but it could also present a starting point for further studies that extend the model to other possible explanatory variables. However, the low R^2 may not only be the consequence of the low number of significant coefficients. Goodness-of-fit is poor, the model does not fit the data well, and this may mean that this model specification could not be a good choice for this analysis. This is another possible limitation of the present study.

On the other hand, the test on the whole bivariate model reveals significance. The only critical issue that seems to have an effect on the quality of distance learning perceived by disabled students (but only for synchronous lessons) is concentration difficulties. This aspect is irrelevant as a predictor of the perceived quality of the videotaped lessons. It can be regarded as related to the specific health condition of disabled students when they attend live lessons in general (Roberts et al., 2011; Re et al., 2014): further proof of this is given by a previous survey about first semester courses, 15% of disabled students complained about difficulty of concentration in face-to-face lessons.

The methodological approach used for the statistical analysis is based on the specification and estimation of a bivariate regression model, on carrying out the MANOVA of the model and testing the importance of the considered factors with a multiple permutation test. It is a flexible and robust solution, valid especially when the assumption of normality or other distribution of the error terms, typical of some parametric methods, is not plausible or not evident. This is true for univariate regression models but in particular for multivariate models because it also takes into account the dependence relationships between the components of the multivariate error (and of the multivariate response) and does not require assumptions about these relationships. The presented simulation study indicates that the permutation MANOVA is a valid solution for the bivariate regression analysis, because the test is well approximated, powerful, unbiased and consistent.

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