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ANTECEDENTS OF DISTANCE LEARNING PERCEPTION OF THE STUDENTS DURING THE COVID-19 PANDEMIC

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Abstract: *The COVID-19 pandemic has affected every aspect of economic and social life, even overwhelming education. The sudden shift from face-to-face to distance learning affected the students' learning experience. In addition to some tangible factors, such as the availability of a good connection or adequate connecting devices, several social and psychological factors may have influenced distance learning students' perceptions. This paper aims to understand how higher education students perceived distance learning during COVID-19 and whether some socio-psychological factors, such as stress and career-related anxiety, impacted their perception. Data are collected from a survey of 1592 students from various Italian Universities and analyzed using exploratory factor analysis and partial least squares-based structural equation modelling.*

Keywords: *Student stress, Career-related anxiety, Distance learning, Exploratory factor analysis, PLS path modeling.*

1 INTRODUCTION

The World Health Organization declared the global pandemic of Corona Virus Disease (COVID-19) infection in March 2020 (World Health Organization, 2020). Lockdowns and social restrictions were subsequently adopted in many countries worldwide to reduce the virus's spread. Nevertheless, the COVID-19 pandemic has become explosive, permeating every sphere of the socio-cultural lives of individuals, clearly including education. Starting from the second semester of the academic year 2019/20, distance learning (DL) was the only possible way of learning for almost all students of any age. The sudden shift from face-to-face to distance learning undoubtedly affected students' learning experiences. Therefore, online education is now becoming critical in students' learning process.

The pandemic has accelerated the transformation of the educational process, and e-learning is taking on an important role. Thus, it would be advisable to understand students' perception of DL and identify the factors that impact this perception. This information is crucial to plan efficient use of e-learning, possibly alongside traditional learning systems.

In addition to some tangible factors, such as the availability of a good connection or adequate connecting devices, several social and psychological factors may influence DL students' perceptions.

COVID-19 has also created a psychological crisis producing anxiety, depression, insomnia, trauma, anger, psychosis, panic, and boredom (American Psychological Association, 2020; Brooks et al., 2020). Some studies dealt with the increasing concern related to students' mental health showing that the COVID-19 pandemic situation delivered the 'next generation' into renewed focus (see Commodari et al., 2020; Son et al., 2020, among others). An undoubtedly relevant role for students is played by anxiety about future career projects, stress related to the fear of contagion and isolation, and changes in their relationships with friends, colleagues, professors, and partners.

First, this paper aims to measure latent concepts such as *student stress*, *future career anxiety*, and *student perspective of DL* using measurement scales already existing in the literature. Second, to extend the discussion in this field by analyzing the relationships between the socio-psychology drivers and the perspective of DL high education students.

To achieve this objective, a survey of 1592 students from various Italian Universities conducted in September – December 2020 is examined. Exploratory Factor Analysis (EFA) (Hair et al., 2006) is used to explore the three scales' latent dimensional structure and Structural Equation Models (SEM) (Bollen, 1989) to investigate the relationships among the identified latent dimensions. The remainder of this paper is structured as follows: Section 2 outlines the methodology by including the EFA in Section 2.4.1, and the SEM in Section 2.5; Section 3 presents the main results, while Section 4 reports the main conclusions and implications.

2 METHODOLOGY

2.1 PARTICIPANTS AND PROCEDURE

To test our research model, we used an online survey conducted by the Department of Political Sciences, University of Naples Federico II, to collect quantitative data from a sizeable number of respondents (students) from 60 universities in Italy. The data collection was done between September – December 2020. Respondents have been randomly selected using a chain sampling where many students enrolled in university associations have been asked to recruit further students among their associates. Students were fully informed about the study's aims and the data's confidentiality. Respondents were also assured that the data would be used only for the research and that refusal to participate in the study would not affect their current and future treatments. Every precaution was taken to protect the privacy of research subjects and the confidentiality of their personal information. The questionnaires were anonymously completed after the acceptance of informed consent. The participant's health, dignity, integrity, and rights were preserved, and data were collected without physical and psychological hazards for the research subjects. The research was performed following the 1964 Helsinki declaration (World Medical Association, 1964) and its later amendments or comparable ethical standards. We did not seek the approval of an ethics committee as it was not a clinical trial, and therefore the respondents' health was not subject to any risk.

A total of 1592 questionnaires were received, with details on respondents' socio-demographic characteristics shown in Table 1.

Table 1: Structure of respondents according to selected socio-demographic characteristics

Variables	*Levels*	*Percentage %*
Gender	Female	74.7
	Male	25.1
	Other	0.2
Work	No	62.4
	Occasional	26.8
	Permanent position	7.3
	Temporary position	3.5
Type of student	Commute	31.6
	Off site	31.8
	On site	36.6
Degree	Bachelor	58.2
	Master	28.4
	Master full	13.4
Field	Arts	3.3
	Economics	14.9
	Humanities	21.9
	Law	7.3
	Medicine	11.6
	Science	29.8
	Social	11.2

The sample was composed of students enrolled in Science (29.8%), Humanities (21.9%), Economics (14.9%), Medicine (11.6%), Social Science (11.2%), Law (7.3%), and Arts (3.3%) degree programs. The more significant proportion of females in the sample is consistent with their greater propensity to participate in online surveys than males (see Smith, 2008).

2.2 MEASURES

The *future career anxiety* scale (Mahmud et al., 2021) in Table 2 is conceived to measure a unidimensional conceptualization of *anxiety* (ANX). It comprises five items (Q51-Q55) on a 4-point Likert scale ranging from one ("strongly disagree") to four ("strongly agree").

The administered questionnaire included many batteries of questions, some of which were not included in this analysis. For this reason, the labels of the variables refer to the location of each question in the questionnaire.

Table 2: The future career anxiety scale

	Measurement items
Q51	I worry about future employment because of a potential economic recession due to the outbreak of COVID-19.
Q52	I worry about future employment because of fierce competition in the job market due to the outbreak of COVID-19.
Q53	I worry about future employment because my salary would probably not be as excellent as I wish for the devastating effect of COVID-19.
Q54	I worry about future employment because of the increasing unemployment and job cut reported by the mass media for the reason of COVID-19.
Q55	I worry about future employment because I probably would not find a job that interests me for the reason of COVID-19.

The *COVID-19 student stress questionnaire* (Zurlo et al., 2020) in Table 3 is assessed to measure the *student stress* (STR) multidimensional conceptualization. It consists of 7 items on a 5-point Likert scale ranging from zero ("not at all stressful") to four ("extremely stressful"). The seven items are grouped into three sub-scales:

i) four items (Q46-Q49) measure stress concerning relationships with relatives, relationships with colleagues, relationships with professors, and academic studying experience (Relationships and Academic Life - ReAcL);

ii) two items (Q45, Q50) measure perceived stress concerning social isolation and changes in sexual life (*Isolation* - Iso);

iii) One single item (Q44) weighs the stress due to contagion risk (*Fear of Contagion* - FeCo).

The scale used to measure the *student's perspective of the DL* (Amir et al., 2020) in Table 4 consists of twelve items on a 4-point Likert scale ranging from zero ("strongly disagree") to three ("strongly agree"). The items are grouped into three sub-scales:

i) two items (Q20, Q21) measure the preference for the DL relative to the clarification sessions and assessments (*Preference Domain* - PreDom);

ii) four items (Q22-Q25) measure the effectiveness of the DL, that is if it creates problems or not if it causes stress if it allows you to have more time to prepare learning materials before group discussion or to review all learning materials after class (*Effectiveness Domain* - EffDom);

iii) six items (Q26-Q31) measure satisfaction with the DL (*Learning Satisfaction Domain* - LsDom).

Table 3: The COVID-19 student stress scale

	Measurement items
	Relationships and Academic Life (RelAcL)
Q47	How do you perceive the relationships with your university colleagues during this period of COVID-19 pandemic?
Q48	How do you perceive the relationships with your university professors during this period of COVID-19 pandemic?
Q49	How do you perceive your academic studying experience during this period of COVID-19 pandemic?
Q46	How do you perceive the relationships with your relatives during this period of COVID-19 pandemic?
	Isolation (Iso)
Q50	How do you perceive the changes in your sexual life due to the social isolation during this period of COVID-19 pandemic?
Q45	How do you perceive the condition of social isolation imposed during this period of COVID-19 pandemic?
	Fear of Contagion (FeCo)
Q44	How do you perceive the risk of contagion during this period of COVID-19 pandemic?

Table 4: The distance learning scale

	Measurement items
	<u>Preference Domain</u> (PrefDom)
Q20	Clarification sessions is more suitable delivered in distance learning.
Q21	Assessment is more suitable delivered in distance learning.
	<u>Effectiveness Domain</u> (EffDom)
Q22	I do not experience any problems during distance learning.
Q23	I do not experience stress during distance learning.
Q24	I have more time to prepare learning materials before group discussion with distance learning.
Q25	I have more time to review all the learning materials after class with distance learning.
	<u>Learning Satisfaction Domain</u> (LsDom)
Q26	Distance learning give similar learning satisfaction than classroom learning.
Q27	Distance learning can be implemented in the next semester.
Q28	Distance learning give motivation for self-directed learning and eager to prepare learning materials before group discussion.
Q29	Communication with lecturers and fellow students is easier with distance learning.
Q30	I like distance learning than classroom learning.
Q31	I study more efficiently with distance learning.

2.3 HYPOTHESES DEVELOPMENT

The present work does not refer to any pre-specified and general theory in the literature. That is a model that has analyzed dependency relationships between the three scales presented in the previous section has never been proposed and validated in the literature. As discussed in Section 1, the goal of this study is to analyze how certain socio-psychological factors influence students' perception of DL. Furthermore, since *career anxiety* assumes both the role of the independent and dependent variables, it is also interesting to analyze its role as a *mediator*. A mediator is a construct (latent variables, LVs) of the structural model that accounts for the relationship between an independent variable (dimensions of the stress) and a dependent variable (dimensions of the DL) (Baron and Kenny, 1986). The main objective of the study is, therefore, to explore the following research hypotheses:

- H1: *A significant relationship exists between stress and anxiety for a future career.*
- H2: *There is a significant impact of stress and career anxiety on distance learning.*

- H3: *Anxiety mediates the relationship between stress and perception of distance learning.*

2.4 ANALYTIC APPROACH

As discussed in Section 2.3, this paper does not aim to confirm a pre-existing theory. For these reason, the analysis followed in this research will be exploratory, aiming at identifying possible relationships between the considered constructs (Henseler, 2021).

2.4.1 EXPLORATORY FACTOR ANALYSIS

The three scales' factor structure is assessed through EFA (Hair et al., 2006; Spearman, 2004). It is one of the most widely used statistical techniques in the social and behavioral sciences to measure survey *constructs*. The exploratory nature of the method is based on the fact that no latent structure is imposed on the observed indicators. Instead, various statistical and interpretation criteria determine the optimal number of factors (Bandalos and Finney, 2010).

The main idea is that the LV cannot be directly observed, but it has a direct influence on each of the observed indicators (manifest variables, MV) so that they can, in turn, be used to gain insights into the LV.

Given p MVs and k underlying factors, the factor model is:

$$\mathbf{x} = \boldsymbol{\Lambda\xi} + \boldsymbol{\delta}, \tag{1}$$

where $\mathbf{x}$ is the vector of observed variables, $\boldsymbol{\Lambda}$ is the matrix of regression coefficients (factor loadings) between indicators and factors, $\boldsymbol{\xi}$ is the vector of LVs, and $\boldsymbol{\delta}$ is the vector of uniqueness (unique variances), i.e. the variability in the MVs not associated with the LVs. Factor loadings are crucial in the interpretation of the factorial solution. They measure the relationship between factors and indicators: high values indicate a greater association between the indicator and the factor.

The factor model in Equation (1) can be used to predict the correlation matrix of the MVs as expressed in:

$$\boldsymbol{\Sigma} = \boldsymbol{\Lambda\Phi\Lambda} + \boldsymbol{\Theta}, \tag{2}$$

where $\boldsymbol{\Sigma}$ is the model-predicted correlation matrix of the items, $\boldsymbol{\Phi}$ is the correlation matrix for the factors, and $\boldsymbol{\Theta}$ is the diagonal matrix of unique variances. Several extraction methods are available to find loadings estimates that will yield $\mathbf{\Sigma}$ as close as possible to the observed correlation matrix. One of the most popular is *principal axis factoring*, which does not require specific distributional assumptions about the indicators. Once EFA has extracted the factors, it generally uses rotation methods to facilitate interpreting the results. Many rotation methods are distinguished, ranging from those based on orthogonal rotations (i.e., varimax) to those found on oblique rotations (i.e., oblimin). The difference between the two is that the oblique rotation relaxes the hypothesis of non-correlation between the factors, sometimes considered too stringent. The *parallel analysis* criterion, proposed by Horn in 1965 (Horn, 1965), will be used in the analysis. The eigenvalues are calculated from many matrices of random data of the same size as the current one. Only factors whose original eigenvalues are larger than the 95th percentile of the eigenvalues should be retained (Longman et al., 1989).

2.5 STRUCTURAL EQUATION MODELS

The relationships among the factors extracted from the EFA are then expressed through structural equation models (SEMs). SEMs are a class of models for analyzing the relationships between LVs that are measured through multiple MVs (Bollen, 1989; Jöreskog, 1978).

Following the conventional notation, the model can be expressed as

$$\mathbf{y} = \mathbf{\Lambda_y \eta} + \boldsymbol{\varepsilon}, \tag{3}$$

$$\mathbf{x} = \mathbf{\Lambda_x} \boldsymbol{\xi} + \boldsymbol{\delta} \tag{4}$$

$$\boldsymbol{\eta} = \mathbf{B}\boldsymbol{\eta} + \mathbf{\Gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{5}$$

where $\mathbf{y}$ is a (p x 1)-dimensional vector containing p endogenous observed variables, $\mathbf{x}$ is a (q x 1)-dimensional vector with q exogenous observed variables, $\boldsymbol{\eta}$ is an (r x 1)-dimensional vector containing r endogenous latent variables, $\boldsymbol{\xi}$ is an (s x 1)-dimensional vector containing s exogenous latent variables; $\boldsymbol{\varepsilon}$ and $\boldsymbol{\delta}$ are error vectors, respectively, of (p x 1) dimensions and (q x 1) dimensions, and $\boldsymbol{\zeta}$ is a residual vector of (r x 1) dimensions; $\mathbf{\Lambda_x}$ and $\mathbf{\Lambda_y}$ are respectively loading matrices of (p x r) and (q x s) dimensions, and $\mathbf{B}$ and $\mathbf{\Gamma}$ are respectively structural coefficient matrices of (r x r) and (r x s) dimensions. Both Equations (3) and (4) form the *measurement model*, whereas Equation (5) represents the *structural model*. An LV is defined as *endogenous* if it occurs as a dependent variable in the structural model; otherwise, it is *exogenous*. The same distinction falls on the corresponding MVs, thus distinguishing between endogenous or exogenous MVs.

SEM estimation methods follow two approaches: the covariance-based approach and the variance-based approach. The maximum likelihood method is the most well-known estimation method for the covariance-based approach (Bollen, 1989). In contrast, partial least squares path modelling (PLS-SEM) is the most developed method for the variance-based approach (Wold, 1982). The present paper follows the variance-based approach: the proposed model is not based on a well-developed and testable theory, and therefore an exploratory approach is advisable.

The three-step consistent PLS (PLSc) algorithm (Dijkstra and Henseler, 2015a) is used to obtain results consistent with a factor model:

1. a first iterative phase is carried out to determine the weights to create scores for each construct;
2. the second step corrects for attenuation in correlations between LVs, thus providing a consistent construct correlation matrix;
3. the third step estimates the model parameters (weights, loadings, and path coefficients).

PLS-SEM offers measures indicating the model's approximate fit, which expresses how similar the empirical and the model-implied variance-covariance matrix are. The standardized root mean square residual (SRMR) allows the discrepancy calculation. The fit of the model improves as SRMR decreases. Hu and Bentler (Hu and Betler, 1999) suggested a value of 0.08 as a reasonable threshold value. In addition to the global model evaluation, local model evaluation is employed to assess the goodness of the measurement model and the structural model.

3 RESULTS

3.1 RESULTS FROM EXPLORATORY FACTOR ANALYSIS

EFA using the *principal axis factoring* extraction method with *oblimin rotation* is carried out on the three scales separately. The Kaiser-Meyer-Olkin measure (Kaiser, 1970) shows that data are adequate for the factor analysis, being greater than the minimum acceptable value of 0.5 for each of the three scales (STR = 0.76; ANX = 0.86; DL = 0.93). *Parallel analysis* is used for determining the optimal number of factors. The results in Figure 1 confirm the ANX scale's one-dimensional nature, while suggesting retaining two factors for STR and DL instead of the three expected by the original scales.

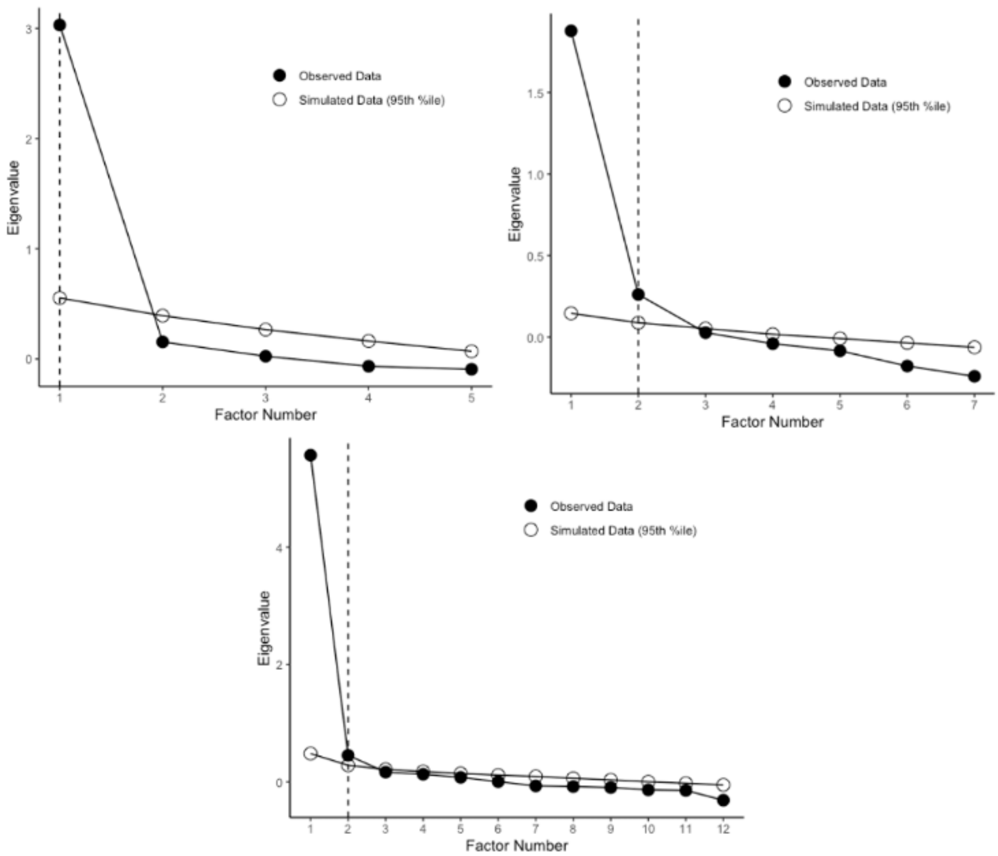

Figure 1: Parallel analysis results from the EFA on the three scales: ANX (top-left), STR (top-right), DL (bottom)

We must detect which variables relate to each extracted factor to interpret the solution. The loadings, representing the correlations between the factors and the variables, provide such information: a high factor loading indicates that a specific factor represents a variable well.

Results of the EFA on the future career anxiety scale are shown in Table 5, which includes the item loadings after rotation and the communalities. The latter indicates how much variance of each manifest variable is explained by the set of extracted factors and should be higher than 0.30 (Costello and Osborne, 2005). The factor (F1) is loaded by all the items, as they all present high factor loadings. Furthermore, all communalities are satisfactory.

Table 5: Results from the exploratory factor analysis on the future career anxiety scale

Factors and Items	*F1*	h^2
F1: Career anxiety		
Q54	0.83	0.69
Q51	0.79	0.63
Q52	0.79	0.62
Q53	0.74	0.55
Q55	0.73	0.54

h^2 is item communality.

The EFA results on the STR scale in Table 6 suggest removing some items (Q44, Q46, Q49, Q50) since they exhibit weak loadings and/or low communalities. Therefore, the first factor corresponds to the *Relationships and Academic Life* subscale, while the second to the *Isolation* subscale. In addition, the factor solution does not highlight the *Fear of contagion* dimension, which was included in the original scale (item Q44).

Table 6: Results from the exploratory factor analysis on the COVID-19 student stress scale

Factors and Items	*F1*	*F2*	h^2
F1: Relationships and Academic Life			
Q48	**0.84**	-0.03	0.68
Q47	**0.64**	0.06	0.46
Q49	0.32	0.30	0.30
F2: Isolation			
Q45	-0.03	**0.72**	0.50
Q44	0.03	0.43	0.20
Q50	0.02	0.38	0.15
Q46	0.15	0.35	0.20

Values in bold indicate major loadings. h^2 is item communality.

The inspection of the DL *factor loadings* in Table 7 shows that the first factor (F1) corresponds to the *Learning Satisfaction Domain* subscale as it is saturated by its respective items but also by two items of the *Effectiveness Domain*, which, however, concerns the sphere of satisfaction (Q22: *I do not experience any problems during DL*; Q23: *I do not experience stress during DL*). On the other hand, the *Preference Domain* subscale is not represented since its indicators (Q20, Q21) are not well explained by the model as both have low communalities. The second factor (F2) reflects the *Effectiveness Domain*.

Table 7: Results from the exploratory factor analysis on the distance learning scale

Factors and Items	*F1*	*F2*	h^2
F1: Learning Satisfaction Domain			
Q30	**0.86**	-0.05	0.69
Q28	**0.82**	-0.06	0.62
Q26	**0.80**	-0.02	0.62
Q27	**0.68**	0.03	0.48
Q29	**0.67**	-0.11	0.36
Q31	**0.67**	0.18	0.64
Q22	**0.60**	0.19	0.54
Q20	0.55	-0.03	0.28
Q23	**0.52**	0.24	0.49
Q21	0.45	0.06	0.24
F2: Effectiveness Domain			
Q25	0.00	**0.81**	0.65
Q24	0.05	**0.79**	0.67

Values in bold indicate major loadings. h^2 is item communality.

3.2 RESULTS FROM SEM

The analysis then continues with the estimation of the model investigating the impact of the socio-psychology drivers on the student perspective of the DL using the PLS-SEM procedure. First, the goodness of model fit is verified using the SRMR as an indicator of approximate model fit. In this study, the SRMR is below the suggested threshold of 0.080, thus indicating an acceptable model fit. This result suggests that the proposed model is suited for explaining the relationship between the student perspective of distance learning and the considered socio-psychology drivers.

The local model assessment is then presented, which consists of evaluating the two components of the SEM, namely the measurement model and the structural model. Figure 2 shows the main results of the whole structural equation model.

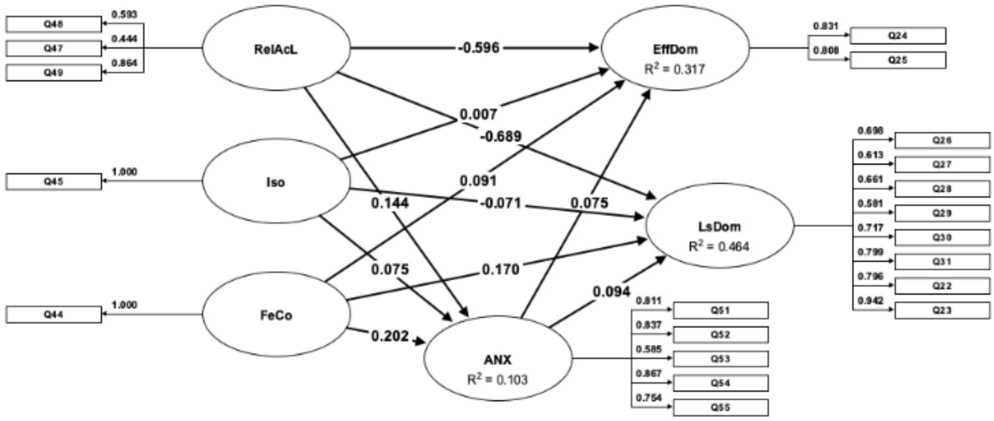

Figure 2: The results of the full SEM

The measurement model's assessment confirms *composite reliability*, *convergent validity*, *indicator reliability* and *discriminant validity*.

The composite reliability measures the variance in the construct scores explained by the latent variable. The Dijkstra-Henseler's ρ_A is used as a consistent estimate of the reliability of construct scores. A value larger than 0.7 is considered reasonable as it indicates that more than half of the variance in the construct scores is explained (Dijkstra and Henseler, 2015b). Results in Table 8 show ρ_A values above the suggested threshold for all constructs.

Individual reliability of each indicator is measured through the squared loading, which measures the proportion of its explained variance. Note that a loading higher than 0.707 indicates that more than 50% of the indicator variance is explained. However, lower values are not a problem when composite reliability and convergent validity are ensured. Figure 2 shows good loadings values for almost all items included in the model.

Convergent validity indicates whether the dominant factor is extracted from the indicators.

For this purpose, the AVE is the most used measure and consists of the average indicator reliability. A value greater than 0.50 would indicate that more than half of the variability of the indicators is explained by the extracted factor, so there cannot be a second factor that explains more. Results in Table 8 show AVE values above 0.50 for all constructs but *Relationships and Academic Life*.

Table 8: Construct composite reliability and convergent validity

Construct	*AVE*	ρ_A
Effectiveness Domain	0.671	0.803
Learning Satisfaction Domain	0.539	0.913
Career anxiety	0.604	0.893
Relationships and Academic Life	0.432	0.744
Isolation	1.000	1.000
Fear of Contagion	1.000	1.000

The discriminant validity is assessed through the correlations' heterotrait-monotrait ratio (HTMT) (Henseler et al., 2015). HTMT values lower than 0.85 indicate that the two considered constructs are statistically distinct. Results in Table 9 show that all constructs satisfy discriminant validity.

Table 9: Construct discriminant validity

Construct	*EffDom*	*LsDom*	*ANX*	*RelAcL*	*Iso*
EffDom					
LsDom	0.688				
ANX	0.040	0.030			
RelAcL	0.534	0.618	0.244		
Iso	0.230	0.317	0.203	0.471	
FeCo	0.057	0.017	0.265	0.300	0.310

Once the measurement model has been assessed, the analysis can evaluate the structural model's results.

According to the R^2 values reported in Figure 2, the three dimensions of COVID-19 student stress explain 10% of the *future career anxiety* variance. In addition, the constructs measuring *future career anxiety* and *COVID-19 student stress* explain 32% of the *Effectiveness Domain* and 46% of the *Learning Satisfaction Domain*.

Results in Table 10 show the estimated path coefficients and the corresponding bootstrap confidence intervals. All direct effects (path coefficients) are significant except the effect of *Isolation* on the *Effectiveness Domain* (CI = [-0.051, 0.068]). The *Fear of Contagion* is the dimension of stress that has the greatest impact on *future career anxiety* ($\hat{\beta}$ = 0.202): as stress increases due to the fear of contagion, the anxiety for future career increases. The *Effectiveness Domain* depends more on *Relationships and Academic Life* ($\hat{\beta}$ = -0.596): as stress in social relationships and academic life increases, the effectiveness of DL decreases. *Learning satisfaction* also decreases with increasing stress in *relationships and academic life* ($\hat{\beta}$ = -0.689) and social isolation ($\hat{\beta}$ = -0.071), while it increases with increasing *fear of contagion* ($\hat{\beta}$ = 0.170) and *anxiety* ($\hat{\beta}$ = 0.094). All these results support hypotheses H1 and H2 reported in section 2.3. Indeed, on the one hand, stress dimensions have a significant effect on anxiety about future careers. But on the other hand, the dimensions of stress, together with concern about the future career, exert a considerable impact on the distance learning dimensions.

Table 10: Path coefficients and their significance level

Predictor	*Response*	*Coefficient*	*Percentile bootstrap quantiles*	
			2.5%	*97.5%*
Fear of contagion	Career anxiety	0.202	0.146	0.258
Isolation		0.075	0.006	0.140
Relationships and Academic Life		0.144	0.072	0.218
Career anxiety	Effectiveness Domain	0.075	0.014	0.135
Fear of contagion		0.091	0.036	0.150
Isolation		0.007	-0.051	0.068
Relationships and Academic Life		-0.596	-0-661	-0.529
Career anxiety	Learning Satisfaction Domain	0.094	0.043	0.144
Fear of contagion		0.170	0.121	0.219
Isolation		-0.071	-0.131	-0.009
Relationships and Academic Life		-0.689	-0.750	-0.634

In addition to direct effects analysis, SEM also offers indirect and total effects analysis. The indirect effects are given by the product of the path coefficients encountered along the path between a predictor and a response variable. If the path is only direct, i.e., no other constructs along the way, then the indirect effect is null; therefore, the total effect will coincide with the direct one. Otherwise, the total effect will be given by the direct and indirect effect sum. Table 11 shows the decomposition of the total effects exerted by the dimensions of stress on the perception of DL. Since almost all indirect effects are significant, the *career anxiety* construct assumes the role of mediator in the relationships connecting the stress and the distance learning dimensions. This result supports hypothesis H3, reported in section 2.3, that anxiety about the future career significantly intervenes in the relationship between the dimensions of stress and the perception of distance learning. Since all indirect effects are positive, although not exceptionally high, the impact of some of the stress dimensions, those with a direct negative effect, is mitigated (RelAcL on both EffDom and LsDom, Iso on LsDom). In contrast, the effect of the dimensions with a direct positive effect is slightly accentuated. This also results from the comparison of direct effects (path coefficients) and total effects.

Table 11: Direct, indirect, and total effects

Predictor	*Response*	*Direct*	*Indirect*	*Total*
Fear of contagion	Career anxiety	0.202		0.202
Isolation		0.075		0.075
Relationships and Academic Life		0.144		0.144
Career anxiety	Effectiveness Domain	0.075		0.075
Fear of contagion		0.091	0.015	0.106
Isolation		0.007	0.006	0.013
Relationships and Academic Life		-0.596	0.011	-0.585
Career anxiety	Learning Satisfaction Domain	0.094		0.094
Fear of contagion		0.170	0.019	0.189
Isolation		-0.071	0.007	-0.064
Relationships and Academic Life		-0.689	0.014	-0.675

All effects are significant at an alpha level of 5% except for the relation Isolation →Effectiveness.

4 CONCLUSION AND IMPLICATIONS

Due to the spread of the COVID-19 pandemic, most countries have turned to distance learning (DL) to safeguard the health of students and teachers. However, several factors have influenced students' perceptions of this type of learning. This study analyzed the influence of two socio-psychological factors: student stress (STR) and future career anxiety (ANX). The research operationalized STR and DL as multidimensional constructs, while ANX is a one-dimensional construct. Therefore, the study hypothesized a direct effect of both socio-psychological constructs on DL. A further hypothesis concerned the mediator role of the ANX construct in the relationship between STR and DL.

This research empirically found that students' effectiveness and satisfaction with DL decrease as stress in relationships and academic life increases. The latter, on the other hand, increases as the fear of contagion increases.

The research findings could be used in optimal planning of the DL by encouraging social relationships between students that guarantee levels of safety and by providing psychological support regarding the fear of contagion.
Future research may extend a multilevel study in the context of structural equation modelling via partial least squares (PLS-SEM). It can be seen as an analysis in which we scrutinize the complex relationships between latent variables on different levels (universities). In addition, it will allow us to study how group membership is expected to influence data analysis results.

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