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DETERMINANTS OF STUDENTS' ATTITUDE TOWARDS ONLINE LEARNING IN HIGHER EDUCATION DURING COVID-19

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Abstract *The emergence of online environments due to the COVID-19 outbreak has changed the landscape of educational learning. The pandemic emotionally affected students around the world: some benefited from online/blended learning, others lost motivation. In this paper, exploiting a structural equation model approach, we report on observed characteristics and latent factors impacting students' attitude toward online/blended learning during the pandemic emergence. The research was carried out at the University of Foggia, Italy, and encompassed 2,420 students after two years of COVID-19 emergency education. The study results have shown how the overall attitude of students is positive towards online learning, but several features have an essential role in influencing this attitude. The main findings are that students with higher motivation and engagement with professors are more prone to favor online learning, while students with higher engagement with classmates and worse pandemic emotional impact exhibit a lower level of satisfaction. Furthermore, considering contingency factors, commuter and working students display a more positive attitude, but the ones enrolled in scientific-technological courses show a lower level of satisfaction with online learning. Considerations and implications of these results are provided.*

Keywords: *online learning, attitude, covid-19, structural equation model*

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1. Introduction

The COVID-19 pandemic has been representing a complex health challenge for the entire world. To reduce the transmission of the coronavirus disease, sev-eral countries established infection prevention and control measures by limiting contact between people. Governments suggested or ordered physical distancing and movement restrictions. As a result of the COVID-19 outbreak, the educational system has moved to deliver courses online during Spring 2020 (Ali, 2020; Daniel, 2020; Hodges et al., 2020; Murphy, 2020), thus online learning rushed pervasively in students' daily life (Ali, 2020; Huang et al., 2020), introducing new organizational challenges for educational institutions (Abdullah and Kauser, 2022; Musella et al., 2022). Some universities were offering *asynchronous* classes where instructors prepare assignments or record lectures, and students can complete them at their own pace (Hodges et al., 2020). Some institutions used *synchronous* learning that occurs at a specific time via a specific medium. In Italy, online learning was expanded from Fall 2020 to Spring 2021 (Appolloni et al., 2021; Favale et al., 2020). Some Italian campuses have extended the period to Fall-Winter 2021 and Spring 2022 as well. Although, during the pandemic, online learning has represented a valid alternative to traditional learning, students have been more exposed to stress and difficulties compared to the traditional face to face teaching approach (Farooqui, 2020). Therefore, universities are interested in understanding how online learning impacts on their students. In general terms, by understanding students' attitudes, challenges, and preferences, universities can develop aiding strategies in case there are further waves of COVID-19 or any other disaster requiring an emergency and sudden transition to remote learning.

The shift towards online education during COVID-19 pandemic has triggered the proliferation of many studies focused on perceived learning outcomes and students' satisfaction in this new learning environment. In this context, the present paper explores Italian University students' perceptions about online learning after COVID-19 government measures ("*stay-at-home*" and/or "*physical distance*"). In particular, we focus on the case of the University of Foggia (south of Italy), a young University (about 20 years since its foundation) with about 12 thousand students.

The goal of our research is to investigate students' attitude towards online learning and the features that impact on such an attitude. Online learning attitude pertains to an individual's inclination toward exerting effort in online learning. Students' attitudes toward educational technology directly impact their learning process (Aguilera-Hermida, 2020). Botero et al. (2018) studied the factors that affect behavioral intentions and the use of mobile-assisted learning in the context of language learning. The research has shown that students' attitude significantly impacts their intention to adopt mobile technology learning. Investigating this kind of attitude is of utmost importance to elaborate and allow decision makers to make the best choices to support students' online education, lowering the barrier to education and building inclusive learning environments.

In this research, we try to answer to the following research questions:

- **RQ1.** Does pandemic emotional impact positively affect student attitude towards online learning?
- **RQ2.** Does engagement affect student attitude towards online learning?
- **RQ3.** Does student motivation affect student attitude toward online learning?
- **RQ4.** Is shyness a factor related to student attitude towards online learning?
- **RQ5.** Do exogenous variables, such as gender, age, enrollment year, student worker and commuter status affect student attitude towards online learning?

In our analysis, we assume that the unobserved constructs (i.e., latent variables) influence ordered polytomous observed variables (i.e., observed indicators) measured using Likert scales. Therefore, to address the previous research questions, we employ a generalized structural equation modeling (GSEM) framework (Muthèn, 1984). Structural equation models (SEMs; Bollen, 1989) allow researchers to model complex relationships, account for measurement error, test theoretical frameworks, and visually communicate their findings. Unlike conventional SEMs, which primarily concentrate on continuous and normally distributed data, GSEM expands its applicability to encompass a wider array of data types, including categorical, count, and even mixed types.

The paper is organized as follows. Section 2 provides an overview of the literature. Section 3 presents and offers details concerning the materials and methodology used for this research. Section 4 highlights our results and provides insights for University to improve the learning environment fitting the educational approach to the students. Lastly, Section 5 concludes the paper with final remarks and future works.

2. Literature review

This section provides an overview of previous papers in the literature that have surveyed students to understand their attitudes towards e-learning. After briefly discussing key or seminal papers on students' attitudes towards online learning, we focus on those published after the COVID-19 outbreak.

Lee et al. (2005) developed one of the first studies investigating students' acceptance of an Internet-based learning medium. The model proposed captures both extrinsic (perceived usefulness and ease of use) and intrinsic (perceived enjoyment) motivators for explaining students' intention to use the new learning medium. The results show that both perceived usefulness and enjoyment significantly and directly impact intention to use, while perceived ease of use did not significantly influence students' acceptance of Internet-based learning.

Mehra and Faranak (2012) developed an 83-item attitude towards e-learning scale on six domains, namely "Perceived usefulness", "Intention to adopt e-learning", "Ease of e-learning use", "Technical and pedagogical support", "E-learning stressors" and "Pressure to use e-learning".

Returning to our primary literature focus, we will now provide a chronological overview of studies published after the pandemic outbreak.

Hussein et al. (2020) performed a qualitative study to investigate undergraduate students' attitudes toward their experience with emergency online learning during the first few weeks of the mandatory shift to online learning caused by COVID-19. Cost and time effectiveness, safety, convenience and improved participation were the most frequently cited positive aspects. At the same time, distraction and reduced focus, heavy workload, problems with technology and the internet, and insufficient support from instructors and colleagues were the most recurrent negative aspects. Serhan (2020) investigated students' attitude towards the use of Zoom in remote learning and their perceptions of its effects on their learning and engagement in comparison to traditional face-to-face teaching. The results suggest that students held a negative attitude toward using Zoom and perceived it as having a detrimental impact on their learning experience and motivation. Flexibility was listed as the main advantage. Rafiq (2020) analyzed students' attitudes toward e-learning in higher education in Pakistan using a Technology Acceptance Model (TAM). The findings show that male students and students at higher levels of education have a more positive attitude towards e-learning. Aguilera-Hermida (2020) found out that students preferred face-to-face learning over emergency online learning. Their results show how attitude, motivation, self-efficacy, and use of technology play a significant role in students' cognitive engagement and academic performance.

Another set of papers considered a more extended period of online/remote learning. Tzafilkou et al. (2021) developed and validated a multidimensional scale to measure remote learning attitude of students. The scale was tested on students from a Greek university. The study highlights how the major impact is due to students' prior experience in distance learning and field of study, while gender and age do not show a significant influence. Law (2021) showed that most students have a positive attitude and are satisfied with online learning delivery concerning learning materials, assessments, communication, technological tools, and technical support. Dikaya et al. (2021) analyzed the relation between students' psychological traits and attitudes toward forced remote learning. The findings indicate that students with a more positive attitude toward forced re-mote learning have a higher percentage of assimilated learning materials during the lockdown. Moreover, the authors found statistically significant associations between interpersonal communicative skills (self-regulation, shyness, alienation, manipulative and cooperative communication styles) and thinking styles (right-hemispheric and integrated), on the one hand, and attitude to remote learning, on the other. Gonzalez-Frey et al. (2021) evaluated students' attitude toward remote learning through qualitative analysis. The gathered data revealed that remote ed-ucation was somewhat worse than regular education, and four themes emerged to be of strict impact on online learning: *(i)* communication between students and faculty, *(ii)* flexibility with assignments, *(iii)* increased virtual interaction, and *(iv)* support. Afroz et al. (2021) investigated students' and teachers' attitudes toward online learning during the COVID-19 situation in Bangladeshi government colleges. Findings reveal that cost and time-effectiveness, safety, convenience, and improved participation were the most frequently cited positive aspects. At the same time, distraction and reduced focus, heavy workload, problems with technology and the internet, lack of ICT knowledge and poor network infrastructure, limited availability of educational resources, low attendance of learners, uncooperative learners and insufficient support from instructors and colleagues were the most recurrent negative aspects. Çelik and Uzunboylu (2022) developed a scale to measure the students' attitude towards distance learning including factors such as usefulness, communication, preference for distance learning, and preference for face-to-face learning. The analysis showed how usefulness and preference for distance learning indicated a positive attitude, while social presence and preference for face-to-face learning indicated a negative one. Gender had no impact on the scale dimensions. Chen et al. (2022) investigated differences in students' attitudes toward remote learning by comparing two cohorts of students: those based in Australia and those in China. Both cohorts were studying the same units with the same group of teaching staff. Australian students preferred remote learning due to its convenience and the availability of video recordings. In contrast, students in China preferred face-to-face learning, possibly due to their lack of prior experience in an English-speaking learning environment and hesitance to engage with lecturers and learning activities. These results show how students accept remote learning in a familiar language and learning environment. In contrast, if the teaching is delivered in a second language using unfamiliar teaching methods, remote learning will require additional scaffolding to enhance the learning experience. Assaf and Nehmeh (2022) evaluated the attitude towards remote learning in Lebanon. The study evidenced that the students felt isolated due to remote learning; in addition, online communication was not helpful in improving learning. Zagkos et al. (2022) measured attitudes of students of five Greek universities towards the distance learning process. The data reflects the substantial agreement of the students that face-to-face teaching cannot be replaced by distance learning, especially when it comes to laboratory training. The consensus is also that remote learning has abased pedagogical relationships between professors and classmates and among the latter as well. Findings indicate that students come to a meeting of minds about the educational inequalities, which are worsened by the lack of digital equipment and undeveloped technological infrastructure. Furthermore, this study reveals a correlation between the responses of the sample and their demographic and social characteristics, something that offers possibilities for additional research. Huang and Wang (2022) examined the effects of student motivation and engagement on students' academic achievement in online learning from the perspective of self-determination theory. The study evidenced how online emergency learning environments satisfying students' psychological needs of autonomy and competence promote optimal motivation, positive engagement and academic achievement. This study also contributed to revealing the sophisticated nature of relatedness satisfaction in the case wherein its specific effects depend on the cultural configuration of the contexts and the specific types of engagement. Moreover, the research evidenced how students' engagement acted as partial or full mediators between the satisfaction of the psychological needs and academic achievement. Specifically, the effects of autonomy and competence satisfaction on students' academic achievement were partially mediated by the extent to which they cognitively, emotionally and behaviorally engaged in online learning activities. Radovan and Makovec (2022) studied students of a Slovenian university, evidencing how home setting/environment affected students' attitudes towards distance learning, their assessment of competence for distance learning, as well as their motivation to study and their sense of being overwhelmed. Thus, more study difficulties, negative attitudes and motivation problems were observed among students who were not provided with adequate study conditions. The study indicates that distance learning has also potential, but this potential can only be realized if all those involved in the process are provided with the right conditions.

From this overview, we deduce that students all over the world acknowledge the utility of online/remote learning, especially as an answer to the pandemic emergence, and that they like its peculiar features such as lessons' video recordings. At the same time, they feel the downsides of remote learning affecting specific categories of students. More importantly, students state that for the majority of learning activities face-to-face modality cannot be replaced entirely.

For the sake of clarity, the key features of the papers included in our overview are described in Table 1.

3. Materials and methods

In this section, we first present the research design offering details on the questionnaire administered. Next, we display and discuss the structural equation model used to analyze the collected data.

3.1. The questionnaire

This research was conducted on a sample of students enrolled at the University of Foggia. The first part of the questionnaire is dedicated to gathering general socio-demographic information of respondents. From the questions in this section, we derived some exogenous variables to be included in our model: *Gender*, *Age*, *Average Mark*, *Working student* (if the students works full time or part time), *Commuter Student* (if the student has daily commute from a city outside Foggia to reach the University facilities). We also derived some artificial variables: *Enrollment Year*, *Disciplinary Area* and *Progress Score*. In the current Italian educational system, several types of graduate programs exist; they also have diverse durations and degree. This makes it difficult to compare the student enrollment year across different programs. To solve this problem, we created a variable, *Enrollment Year*, where the students enrolled in the first three years of the higher degree are indicated by their actual enrollment year, while all the others (students in supplementary years or enrolled in Master's degrees) are indicated with 4. For example, a student enrolled in the second year of study, is indicated with 2. A

Table 1: Studies on attitude of students towards online learning published after the COVID-19 outbreak.

Study	Number of partecipants	Main remarks
Aguilera-Hermida (2020)	270 (89% from USA University, 11% otherwise)	Analysis of acceptance of emergency online learning.
Hussein et al. (2020)	45 from University of Abu Dhabi	Qualitative investigations of strength and weakness of emergency remote learning.
Rafiq (2020)	2160 from Pakistan Universities	Application of Technology Acceptance Model to analyze attitude towards e-leaning in higher education.
Serhan (2020)	31 from a USA University	Investigating student attitude toward remote learning via Zoom.
Afroz et al. (2021)	100 from Bangladeshi Government Colleges	Analysis of students' and teachers' attitudes towards online learning.
Dikaya et al. (2021)	280 students from a Russia University	Analysis of students psychological traits (self-regulation, shyness, alienation, manipulative and cooperative communication styles) and attitude toward emergency remote learning.
Gonzalez-Frey et al.(2021)	93 from a college (unspecified institution)	Qualitative analysis of students' attitude.
Law (2021)	97 from Kuching (Malaysia)	Relation between attitude and learning materials, assessments, communication, technological tools and technical support.
Tzafilkou et al. (2021)	142 from a Greece University	Tested a scale to measure remote learning attitude.
Ferrer et al. (2022)	574 (usable)	Relation of Attitude with Engagement, Motivation and Study Mode.
Huang and Wang (2022)	14,935 across 39 universities	Measured participants' perceptions of needs satisfaction, engagement and academic achievement, respectively, during the emergency online learning.
Assaf and Nehmeh (2022)	928 Grade 9 and Third Secondary learners a of formal academic learning in the Lebanese educational system	Evaluation of learners attitude toward remote learning in Lebanon.
Çelik and Uzunboylu (2022)	384 for Exploratory Factor Analysis + 305 for Confirmatory Factory Analysis	Development of a scale to measure attitude towards remote learning.
Chen et al. (2022)	368 from Australia Universities + 40 from China Universities	Comparison of attitude towards online learning between students in Australia and China.
Radovan and Makovec (2022)	1,827 from Faculty of Arts at the University of Ljubljana, Slovenia	Analysis of correlation of attitudes and experience about distance education with variables such as living conditions, study conditions, gender, etc.
Zagkos et al. (2022)	807 from 5 Greece-based universities	Measure of students' attitude toward online learning.

student in his first supplementary year is indicated with 4, as well as a student enrolled in his second year of a Master's degree. The main reason behind this coding is to evaluate the difference between novel students in the university system and experienced students who are confident with the university educational system. *Disciplinary Area* has been derived from the program the students were enrolled in. We grouped their courses by disciplinary area according to the official directives of the Italian Ministry of Education. The variable *Progress Score* is computed as the ratio of the number of credits acquired to those required. It ranges from 0 to 1, with a mean value equal to 0.50 and standard deviation of

0.21. Students in supplementary years are penalized by increasing of the ratio's denominator: the penalty is equal to the number of credits required for an additional year of study.

To measure respondents' traits, we considered several scales proposed in the literature. Building a questionnaire of this type is challenging because it should "optimize" a series of criteria. On the one hand, the questionnaire must pursue the research aims; on the other hand, it must ensure that respondents do not spend too much time and effort in taking it. This maximizes the number of participants that join the research and minimizes the number of responses and incomplete questionnaires. Moreover, some scales needed to be adapted to the context of Italian university and educational environment. To pursue this aim and maximize students' involvement, we picked a subset of questions from each scale corresponding to the most relevant questions for each factor.

Student attitude toward online learning is assessed through a Likert type scale (see Table 2) derived from the work of Serhan (2020).

An aspect considered relevant to explain attitude toward online learning is shyness. Shyness as a personality trait may be defined as excessive self-focus characterized by negative self-evaluation that creates discomfort or inhibition in social situations and interferes with pursuing one's interpersonal or professional goals (Henderson et al., 2010). The nature of online learning impacts the possibility of interaction with others, therefore shy students might have different attitudes towards online learning. Shyness is measured by means of a 6-item Likert scale (see Table 3) based on McCroskey and Richmond (1982).

Another important aspect of our analysis is engagement with professors and with other students. These latent traits are measured through a scale (see Table 4) derived from the work of Freda et al. (2021). Engaged students are not just students who simply attend and participate in lessons, but they are able to sustain efforts, commitments, self-regulate behaviors and choices, negotiate and share their goals with others (colleagues, peers, teachers, families, etc.), accept the challenge of their limits in learning processes (Freda et al., 2021). Students' engagement is generally associated with a positive view of their own study activity, not illusory optimistic, but capable of showing and developing resources in terms of industriousness, activity and initiative (Freda et al., 2021). The engagement with other peers is a relevant aspect of engagement in educational context, and in this study we consider this could have a role in students' attitude towards online learning. Engagement with professors is another aspect of educational engagement, and involves the relationship with the teachers.

Emotional impact of the pandemic is measured by means of the scale provided by Ballou et al. (2020). This scale has been adapted considering the different moments we asked participants to answer, so they were asked to compare their current status to the one previous the COVID-19 outbreak. The scale is composed of 8 items (see Table 5). Global pandemic introduced unprecedented fear/worry about one's own safety as well as the health and safety of all; fears about local and global economic/political instability; frustration/disappointment regarding the complete disruption of daily activities (Ballou et al., 2020). The scale measures the emotional impact of the present pandemic over individuals. More negatively affected people could have more concerns in attending crowded places such as a classroom.

All the items in the scales above are measured on a 5-point rating scale.

The last scale, based on Vallerand et al. (1992), measures students' motivation to attend university. This scale has been validated in Italian by Alivernini and Lucidi (2008). From the original scale we picked 4 out of 6 factors (i.e., Amotivation, Extrinsic motivation – external regulation, Extrinsic motivation – Introjected, Extrinsic Motivation - Identified), with 3 items each. Students were asked if the items matched the reasons they enrolled at university, providing a score between 1 (Matches perfectly) and 7 (It doesn't match at all) (see Table 6). Individuals are amotivated when they do not perceive contingencies between outcomes and their own actions. Amotivated individuals believe that external causes beyond their own control are to blame for their actions. They start doubting themselves and wonder why attending university in the first place.They might quit taking part in academic activities (Deci and Ryan, 1985; Vallerand et al., 1992). Extrinsic motivation pertains to a wide variety of behaviors which are involved as a means to an end and not for their own sake (Deci, 1975; Deci and Ryan, 1985; Vallerand et al., 1992). Extrinsic motivation can be distinguished in three types, ordered from lower to higher level of self-determination: *External Regulation*, *Introjection*, and *Identification*. *External Regulation* occurs when the behavior is regulated through external means, such as rewards and constraints (Deci and Ryan, 1985, 1990; Vallerand et al., 1992). *Introjection* occurs when students internalize the reasons of their actions and act to behave as good students are supposed to do (Vallerand et al., 1992). *Identification* occurs when the behavior becomes valued and judged important for the individual, especially that is perceived as chosen by oneself (Vallerand et al., 1992).

In our questionnaire, we also included an open-ended question, asking the students their opinion on their online learning experience.

The choice of the described latent variables aims to better understand what are the factors that affect the most the attitude of students towards online learning. Motivation is an important factor to have success at higher school (Nur'aini et al., 2020). Personal traits, such as shyness, could have a relevant role in making the students more comfortable at home – typical learning setting for online learning – as they do not perceive the reduction of social opportunities as relevant as the others. Engagement is another driving factor for students' attitude (Ferrer et al., 2022; Sanders et al., 2016), and we aimed to analyze how the engagement with professors and peers interacts with this factor. Finally, we wanted to understand what relation is present between students with negative emotional impact and their attitude towards online learning.

The questionnaire has been submitted through academic emails to all the students: 2,420 of them participated between 24 May 2022 and 14 June 2022. For the University of Foggia, such a time range matches the end of the term, just before the exam session.

Before participating in the survey, all participants provided informed consent with respect to the research scope, and the management and gathering of anonymous data. No compensation was provided for participating in the study.

3.2. Structural Equation Modeling

In our study, we employ a GSEM (Muthèn, 1984) to examine the connection between the endogenous latent variable "attitude towards online learning" and the exogenous latent and observed variables detailed in Section 3.1.

A classical SEM consists of two components: a measurement model that clarifies the relationship between continuous latent variables and their continuous observed indicators, facilitating the estimation of latent factors, and a structural model that illustrates the interactions between endogenous and exogenous variables. When dealing with ordered categorical items, such those obtained through Likert scales, the conventional measurement model, which relies on continuous observed indicators, necessitates the incorporation of a threshold model. This threshold model links each observed categorical indicator to an underlying continuous variable defining specific cut-off points on the continuous underlying variable, which correspond to different response categories on the observed categorical item. The threshold model essentially serves as a bridge that quantifies how the responses on a categorical scale are associated with the unobserved latent construct. This adaptation leads to a GSEM.

In our specification, we assume that there is one endogenous latent variable (namely, η: attitude toward online learning) and eight exogenous latent variables $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_Q)'$.

Denoting by $\mathbf{Y} = (Y_1, \ldots, Y_K)'$ the observed categorical variables measuring the endogenous latent variable η, and with $\mathbf{Z}^{(y)} = \left(Z_1^{(y)}, \ldots, Z_K^{(y)}\right)'$ the corresponding underlying continuous variables, the reflective measurement model for the endogenous latent variable can be expressed as

$$\mathbf{Z}^{(y)} = \boldsymbol{\lambda}^{(y)}\eta + \boldsymbol{\epsilon}^{(y)}, \quad \text{with} \quad Y_k = c \quad \text{if } \gamma_{k,c-1}^{(y)} \leq Z_k^{(y)} \leq \gamma_{k,c}^{(y)},\ k = 1, \ldots, K \tag{1}$$

where the K-dimensional vector $\boldsymbol{\lambda}^{(y)} = \left(\lambda_1^{(y)}, \ldots \lambda_K^{(y)}\right)'$ contains the factor loadings.

Along the same lines, denoting by $\mathbf{X} = (X_1, \ldots, X_L)'$ the observed categorical variables measuring the $Q = 8$ exogenous latent variable $\boldsymbol{\theta}$, and with $\mathbf{Z}^{(x)} = \left(Z_1^{(x)}, \ldots, Z_L^{(x)}\right)'$ the corresponding underlying continuous variables, the reflective measurement model for the exogenous latent variables can be expressed as

$$\mathbf{Z}^{(x)} = \boldsymbol{\Lambda}^{(x)}\boldsymbol{\theta} + \boldsymbol{\epsilon}^{(x)}, \quad \text{with} \quad X_l = c \quad \text{if } \gamma_{l,c-1}^{(x)} \leq Z_l^{(x)} \leq \gamma_{l,c}^{(x)},\ l = 1, \ldots, L. \tag{2}$$

Here, in a confirmatory perspective, the pattern of fixed and free loadings in the $L \times Q$ factor loadings matrix $\boldsymbol{\Lambda}^{(x)}$ is specified according to a multi-unidimensional schema (Sheng and Wikle, 2007), also known as independent cluster structure (McDonald, 2000), where each item loads only on a specific latent variable. Within our model, we assume correlations between the exogenous latent variable.

In equations (1) and (2), $\gamma_{k,0}^{(y)} = -\infty \leq \gamma_{k,1}^{(y)} \leq \ldots \leq \gamma_{k,C}^{(y)} = \infty$ and $\gamma_{l,0}^{(x)} = -\infty \leq \gamma_{l,1}^{(l)} \leq \ldots \leq \gamma_{l,C_l}^{(x)} = \infty$ are the ordered thresholds for item Y_k and X_l respectively, and $\boldsymbol{\epsilon}^{(y)}$ and $\boldsymbol{\epsilon}^{(x)}$ are normally distributed errors.

The structural component of the model can be written as:

$$\eta = \boldsymbol{\beta}'\boldsymbol{\theta} + \mathbf{g}'\mathbf{w} + u \tag{3}$$

where $\boldsymbol{\beta}$ and $\mathbf{g}$ are vectors of regression coefficients, $\mathbf{w}$ is the observed exogenous covariate vector, and u is a normally distributed error.

The structural component is represented in the path diagram provided in Figure 1, where rectangles symbolize the observed exogenous covariates, while ovals rep-resent both endogenous and exogenous latent variables.

4. Results

In this section, we show the results of our study. In more details, we first offer an overview of the participants in our study (Section 4.1); then, we show the

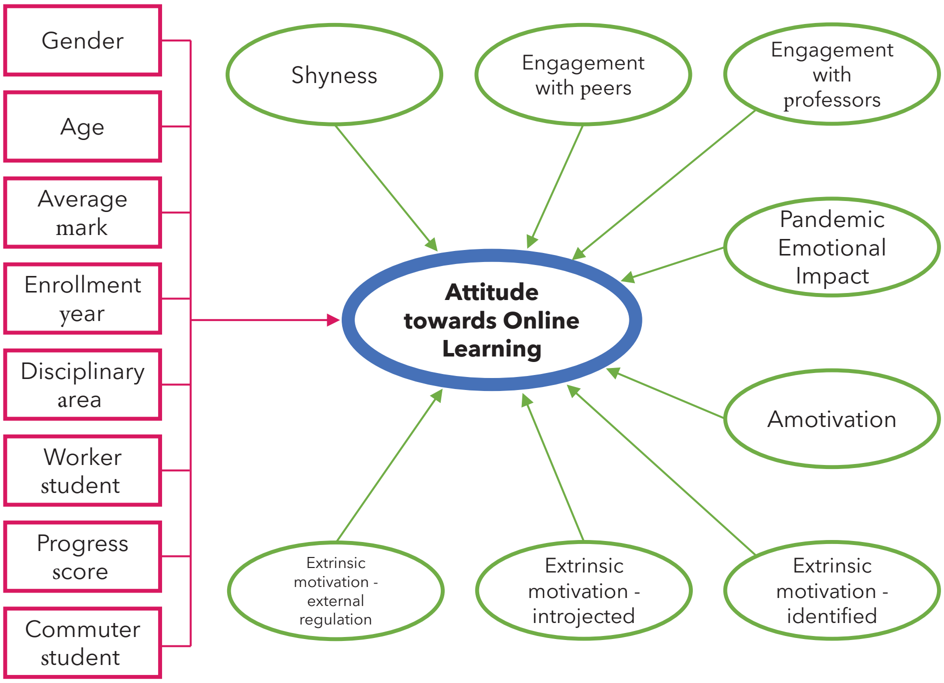


Figure 1: Path diagram for the structural component in the proposed GSEM. ***Rectangles symbolize the observed exogenous covariates, while ovals represent both endogenous and exogenous latent variables.***

results of the measurements model, i.e., how the items impact on the estimates of latent factors (Section 4.2), and the structural relation between the exogenous latent variables and attitude towards online learning (Section 4.3). Next, Section 4.4 is devoted to presenting the findings of this research with regards to the research questions proposed in the introduction. Lastly, in Section 4.5, we report the analysis made on the students' opinions expressed in natural language.

The GSEM estimation here reported has been performed through the R package *lavaan* (Rosseel, 2012), a well-tested library that provides the essential tools for SEM analysis. To deal with the ordinal nature of the observed indicators in the measurement model, we use the weighted least squares mean-and variance-adjusted (WLSMV) estimator, which is the most common method in the SEM literature to analyze ordered categorical variables (see Li, 2016, and references therein). WLSMV is a limited information estimation method that for ordered categorical indicators utilizes polychoric correlations. As a limited information method, WLSMV is not only a robust method but also computationally fast, especially when the sample size and the number of dimensions are large (Flora and Curran, 2004).

The model with 323 parameters has been estimated with 2,016 observations after pruning incomplete observations. We remark we have dropped from the study the students that declared "other" as *gender*, since they were just 6.

4.1. Sample composition

The sample of respondents covers 18% of the students' population. In the Economics, Management, Territory department, the coverage peaks 35% while the lowest value is 13% for the department of Clinical and Experimental Medicine (see Figure 2). Therefore there is broad coverage of all departments.

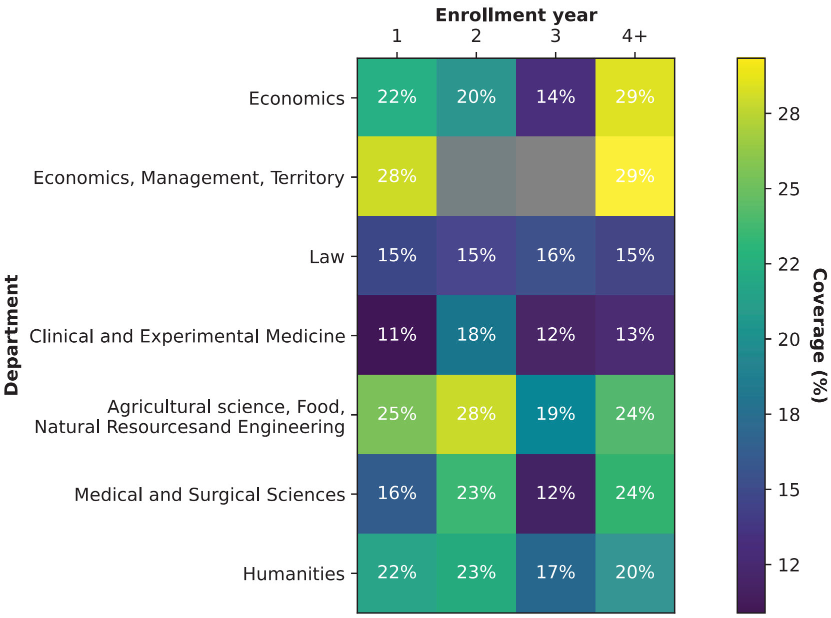
70.5% of respondents are females, 29.2% males, and 0.3% other, covering the 20% of the female population and the 15% of the male population). The mean age of participants is 25 years. 70.9% of respondents are commuters, 17.6% of them are from Foggia city, and the remaining 11.5% are students from outside Foggia which had taken accommodation in the city. 97% declared that they owned adequate devices for online learning and 93% said they had an adequate connection. 70.3% of respondents are enrolled in a Bachelor program, while 16.3% is in a Master's program. The remaining 13.4% is enrolled in a Unique cycle master's degree (5-6 years).

4.2. Measurement equation estimates

Tables 2 - 6 show the estimates of the factor loadings of the measurement equations, along with the ordinal alpha coefficient (Zumbo et al., 2007) for each dimension. Ordinal alpha is conceptually equivalent to Cronbach's alpha (Cronbach, 1951). The critical difference between the two is that ordinal alpha is based on the polychoric correlation matrix, rather than the Pearson covariance matrix, and thus is more suitable to assess the reliability of scales with ordinal indicators. Since all latent variables exhibit ordinal alpha coefficients exceeding 0.75, it can be inferred that the measurement instrument demonstrates high reliability. Furthermore, all the factor loadings are significant with p-value < 0.001. The negative factor loadings are related to items that measure the latent trait in a reverse direction. The estimated threshold parameters are provided in Table A1 in the Online Resource.

Table 7 shows the correlations across the exogenous latent variables in the proposed GSEM.

Figure 2: Coverage of respondents respect the number of enrolled students by department and year of enrollment in higher education.



- Gray background indicates course year without enrolled students (due to a new department).
- Master's degree students have been offset to 4th year, as they require a 3-year bachelor's program to enroll in a master's course.

The highest correlations are observed among the latent variables associated with the *Extrinsic motivation* subscales. This highlights a clear positive relationship between behaviors driven by external rewards and constraints (*External regulation*), and the internalization (*Introjection*) and identification (*Identified*) with the importance of university studies. Moreover there is a moderate negative correlation between *Extrinsic motivation – Identified* and *Amotivation*. This shows that the higher is the self-determination level the lower the propensity to be amotivated. *Amotivation* is directly correlated with *Pandemic emotional impact*, indicating that students experiencing a more severe emotional impact tend to be more amotivated.

We also find a positive correlation between *Engagement with professors* and *Engagement with peers*. Both these forms of engagement are inversely correlated with *Amotivation*, and directly correlated with *Extrinsic motivation - Identified*. These findings emphasize how engagement levels vary with the degree of

Table 2: Measurement model for the latent variable *Attitude toward online learning*: factor loading estimates. The question prompts the students to indicate their agreement with the items.

Id.	Item	Factor Loading Estimate
Factor: ATTITUDE TOWARDS ONLINE LEARNING		
A1	I enjoyed using the online learning platform during the class.	1.000
A2	I would like to use online learning platform in other classes.	1.038
A3	The use of online learning platform allowed flexibility in my learning schedule.	1.007
A4	Overall, I enjoyed using online learning platform in the class	1.029
A5	The use of online learning platform helped me learn the class content.	1.029
A6	The use of online learning platform helped me develop confidence in the subject.	1.030
A7	The use of online learning platform helped me participate in the class in ways that enhanced my learning.	1.031
A8	The use of online learning platform motivated me to actively participate in class activities.	1.039
A9	The use of online learning platform made it easier for me to be more engaged in the class discussions.	1.044
A10	The use of online learning platform increased my interaction with my instructor.	1.020
A11	The use of online learning platform increased my interaction with my classmates.	0.964
A12	The use of online learning platform motivated me to seek help from tutors, classmates, and the instructor.	0.959
A13	The activities during online learning platform sessions motivated me to learn the class content more than the ones in the face-to-face traditional class meetings.	1.012
A14	I participated more in the online learning platform sessions in comparison to the traditional face-to-face class meetings.	0.991
A15	My attention to the class tasks during the online learning platform sessions was greater in comparison to the traditional face-to-face class meetings.	0.999
A16	It was easier to participate in group activities in the online learning platform sessions in comparison to the traditional face-to-face class meetings.	0.986
Ordinal alpha= 0.986		

All the free items estimates are significant with p-value < 0.001.

self-determination. Students who are less inclined to attribute their outcomes to external factors and are more motivated by future career prospects and job market-relevant skills display higher levels of engagement. *Engagement with peers* is inversely correlated with *Shyness*, and this relation is expected, as more shy persons are less likely to engage with others.

4.3. Structural component estimates

Table 8 shows the estimated regression coefficients for the structural component.

Shyness, *Engagement with professors*, *Extrinsic motivation - Introjected* positively affect *Attitude towards online learning*. *Engagement with peers* shows a negative impact: students with higher engagement with their colleagues are less satisfied with online learning.

Table 3: Measurement model for the latent variable *Shyness*: factor loading estimates. The question prompts the students to indicate how much the sentences apply to themselves

Id.	Item	Factor Loading Estimate
Factor: SHYNESS		
B1	I am a shy person.	1.000
B2	Other people think I talk a lot.	-0.346
B3	I tend to be very quiet in class.	1.159
B4	I am a quiet person.	1.266
B5	I talk more in a small group (3-6) than others do.	0.729
B6	I talk more in class than most people do.	-0.597
Ordinal alpha= 0.768		

All the free items estimates are significant with p-value < 0.001.

Table 4: Measurement model for the latent variables related to the *Engagement*: factor loading estimates. The question prompts the students to indicate how much the sentences apply to themselves.

Id.	Item	Factor Loading Estimate
Factor: ENGAGEMENT WITH UNIVERSITY PROFESSORS		
C1	My teachers are interested in my opinions and what I say.	1.000
C2	Teachers are usually available to discuss my work.	1.095
C3	Teachers clarify what they expect of us students.	0.994
Factor: ENGAGEMENT WITH UNIVERSITY PEERS		
D1	I feel like I'm part of a group of friends at University.	1.000
D2	I like to meet friends at university.	0.987
D3	I've made meaningful friends with some college colleagues.	1.077
D4	I have good relationships with my University colleagues.	1.113
D5	Studying with other students is useful to me.	0.671
ENGAGEMENT WITH UNIVERSITY PROFESSORS: **Ordinal alpha=** 0.837		
ENGAGEMENT WITH UNIVERSITY PEERS: **Ordinal alpha=** 0.896		

All the free items estimates are significant with p-value < 0.001.

Extrinsic motivation – Identified has a negative impact on the attitude. Instead, *Amotivation* does not seem to influence attitude toward online learning.

Pandemic impact negatively affects *Attitude towards online learning*. We initially expected students significantly impacted by the pandemic to hold a more positive attitude towards online learning. This anticipation was based on the fact that online classes are typically taken from the safety of one's home, potentially reducing exposure to COVID-19 by avoiding crowded places. However, the coun-

Table 5: Measurement model for the latent variable *Pandemic Emotional Impact*: factor loading estimates. The question prompts the students to indicate how much the sentences apply to themselves, comparing the current status to the one previous the COVID-19 outbreak.

Id.	**Item**	**Factor Loading Estimate**
Factor: PANDEMIC EMOTIONAL IMPACT		
E1	Feeling more frustrated about not being able to do what you usually enjoy doing	1.000
E2	Having more difficulty concentrating	1.359
E3	Feeling more grief or sense of loss	1.417
E4	Being less productive	1.415
E5	Feeling more angry or irritated	1.362
E6	More difficulty sleeping	1.166
E7	Feeling more lonely or isolated	1.269
E8	More anxious	1.210
Ordinal alpha= 0.941		

All the free items estimates are significant with p-value < 0.001.

terintuitive results obtained from our analysis might be attributed to the general low mood of students. It's also possible that a bidirectional effect, not accounted for by the model, could exist, where a negative attitude towards online learning worsens the impact of the pandemic.

Concerning the exogenous variables, male students show a more negative *Attitude towards online learning*. Being an older student has positive impact. As expected, Working Students (both Full-Time and Part-Time) have a more positive attitude. The impact of *Average mark*, *Enrollment year* and *Progress score* is not significant. In the disciplinary area, only scientific technological courses have a significant negative impact on student attitude.

4.4. Findings related to Research Questions

In the following, we provide answers for the research questions discussed in Section 1. We remark that the SEM method adopted has proved to be effective in answering in a comprehensive way to the research questions.

RQ1. ***Does pandemic emotional impact positively affect student attitude towards online learning?*** *Pandemic emotional impact* has a significant relevance in explaining attitude towards online learning with an estimated negative effect. A bidirectional effect could also be possible, given that a negative experience in

Table 6: Measurement model for the latent variables related to the *Motivation*: factor loading estimates. The question prompts the students to indicate how much the sentences match the reasons they enrolled in University.

Id.	Item	Factor Loading Estimate
Factor: AMOTIVATION		
F1	Honestly, I don't know; I really feel that I am wasting my time in school.	1.000
F2	I once had good reasons for going to college; however, now I wonder whether I should continue.	1.064
F3	I can't see why I go to college and frankly, I couldn't care less.	1.009
Factor: EXTRINSIC MOTIVATION - EXTERNAL REGULATION		
F4	Because with only a high-school degree I would not find a high-paying job later on.	1.000
F5	In order to obtain a more prestigious job later on.	1.990
F6	Because I want to have "the good life" later on.	2.127
Factor: EXTRINSIC MOTIVATION - INTROJECTED		
F7	To prove to myself that I am capable of completing my college degree.	1.000
F8	Because of the fact that when I succeed in college I feel important.	0.913
F9	To show myself that I am an intelligent person.	1.020
Factor: EXTRINSIC MOTIVATION - IDENTIFIED		
F10	Because I think that a college education will help me better prepare for the career I have chosen.	1.000
F11	Because eventually it will enable me to enter the job market in a field that I like.	0.994
F12	Because I believe that a few additional years of education will improve my competence as a worker.	0.966
AMOTIVATION: **Ordinal alpha**= 0.926		
EXTRINSIC MOTIVATION - EXTERNAL REGULATION: **Ordinal alpha**= 0.831		
EXTRINSIC MOTIVATION - INTROJECTED: **Ordinal alpha**= 0.911		
EXTRINSIC MOTIVATION - IDENTIFIED: **Ordinal alpha**= 0.892		

All the free items estimates are significant with p-value < 0.001.

an online learning environment might increase the emotional negative impact of the pandemic.

RQ2. ***Does engagement affect students attitude towards online learning?*** Both *Engagement with professors* and *Engagement with peers* significantly impact the attitude. *Engagement with Professors* has a positive effect; therefore, students experiencing higher engagement with professors are more prone to evaluate positively the online learning experience. This can indicate that the relationship between students and professors is essential and affects the appreciation of the deployed learning approach. Instead, *Engagement with peers* has a negative effect; therefore, students that have a better relationship with other students feel it more difficult to adapt to an online learning context. This result is expected because

Table 7: Correlations between the latent variables.

Latent Variable	1.	2.	3.	4.	5.	6.	7.
1. Shyness							
2. Engagement with Professors	−0.061*						
3. Engagement with Peers	−0.297**	0.372**					
4. Pandemic Emotional Impact	0.184**	−0.182**	−0.053*				
5. Amotivation	0.231**	−0.362**	−0.301**	0.418**			
6. Extrinsic Motivation - External Regulation	0.037	0.064*	0.029	0.062	0.166**		
7. Extrinsic motivation – Introjected	0.005	0.117**	0.128**	0.068**	−0.028	0.522**	
8. Extrinsic Motivation - Identified	−0.054*	0.248**	0.206**	−0.067**	−0.319**	0.666**	0.639**

° p-value < 0.10, * p-value < 0.05, ** p-value < 0.01

Table 8: Results of the GSEM Structural component: estimated impact on *Attitude towards Online Learning*.

Regressor	Regression coefficient estimate	Std.Err	z-value	P(>|z|)
Shyness	0.086	0.033	2.614	0.009
Engagement with Professors	0.177	0.035	5.064	0.000
Engagement with Peers	-0.112	0.030	-3.764	0.000
Pandemic Emotional Impact	-0.270	0.040	-6.729	0.000
Amotivation	-0.008	0.059	-0.133	0.894
Extrinsic motivation – External Regulation	0.257	0.114	2.258	0.024
Extrinsic motivation – Introjected	0.164	0.035	4.617	0.000
Extrinsic motivation – Identified	-0.130	0.068	-1.906	0.057
Gender	-0.104	0.048	-2.173	0.030
Age	0.012	0.003	3.914	0.000
Worker Full Time	0.266	0.074	3.577	0.000
Worker Part Time	0.223	0.050	4.463	0.000
Commuter Student	0.204	0.047	4.305	0.000
Average Mark	0.012	0.010	1.157	0.247
Enrolled at first year	0.020	0.060	0.325	0.745
Enrolled at second year	0.011	0.061	0.176	0.860
Enrolled at third year	-0.042	0.068	-0.619	0.536
Disciplinary Area Medical	-0.049	0.078	-0.627	0.531
Disciplinary Area Sanitary	-0.094	0.085	-1.108	0.268
Disciplinary Area Scientific-Technological	-0.121	0.055	-2.195	0.028
Progress Score	0.107	0.120	0.893	0.372

For *Gender*, the baseline is female.
For *Worker Full Time* and *Worker Full Time*, the baseline is the student is not a worker.
For *Worker* status, the baseline is not a worker.
For the year of *Enrollment* the baseline is enrollment in a year over the third.
For the *Disciplinary Area* the baseline is enrollment in a Humanities Area course.

online methodologies provide fewer opportunities to establish relationships with colleagues than traditional learning in classrooms (Kaufmann and Vallade, 2022).

Such a finding could indicate that efforts are needed to compensate for this factor. The literature provides a handful of tools for facing this issue: from the community of inquiry framework – a well-known approach – for building collaborative online learning environments (Fiock, 2020), to the limitless possibilities offered by the so-called "metaverse", where learners will move away from online learning as we know today to more immersive content based on virtual reality tools, gamified learning with an increased engagement (Phakamach et al., 2022).

RQ3. ***Does student motivation affect students attitude toward online learning?*** The impact of motivation on attitude is not equal among all different aspects of motivation evaluated through the scale exploited in our research. Amotivation, which is a lack of perception of contingencies between outcomes and one's actions, does not affect the evaluation of online learning. Students with higher extrinsic motivation for studying tend to have a more positive attitude towards online learning, particularly when their motivation is associated with external factors such as the belief that a university degree will lead to a job. This motivation is prevalent among students who primarily view university as a means of obtaining an academic title. It is noteworthy to examine the result for *Extrinsic motivation - Identified*. Unlike other extrinsic motivations, this type shows an opposite trend—it has a negative effect on attitudes toward online learning. We suspect this is because highly motivated students view the university as a place to acquire knowledge, skills, and competencies that enhance their well-being and career prospects. This perspective suggests that highly motivated students may not perceive online learning outcomes as effectively as traditional methods.

RQ4. ***Is shyness a factor related to student attitude towards online learning?*** As shown in Section 4, *Shyness* has a positive impact on how online learning is experienced: students with a higher level of shyness are more prone to give a favorable evaluation of online learning.

RQ5. ***Do exogenous factors, as gender, age, enrollment year, student worker, and commuter status affect attitude towards online learning?*** The results evidence how the enlisted exogenous features significantly impact the attitude towards online learning. In particular, male students, older students, working students and commuter students are more favorable towards online learning. These results are reasonable: workers students and commuters are the ones experiencing the most significant difficulties in attending face-to-face classes. The online learning, jointly with the recorded lessons, provided them all the flexibility to attend the lessons. The average mark does not result to be significant, while it is interesting how students enrolled in disciplinary courses in the scientific-technological Area seem to be less favorable towards online learning. This is in line with the findings of other studies (Newsome et al., 2022; Ngah et al., 2022; Owston et al., 2020), that discovered how STEM students' perception was worse than non-STEM courses. The University of Foggia was already experimenting with forms of online learning before the COVID-19 outbreak in humanities courses, preparing teachers and adapting courses to this scope. Instead, other programs suffered a rush emergency transition, which may be a possible reason for the different of impact. The *Average mark*, the *Progress score*, and the *Year of enrollment* do not seem to be significant in explaining the attitude toward online learning.

4.5. Textual analysis

Textual questions are intriguing because they allow respondents to freely express their opinions, but they are more challenging to analyze than conventional structured inquiries because they cannot be processed quantitatively. Text mining has been used to approach this type of data. Text mining is a toolbox of methods that enables the extraction of knowledge from text-based data. In this case, we used a bi-gram method to extract information from students' comments. In such an instance, the individual responses are seen as an ordered list of words. A bi-gram consists of two sequential words in a document. From the document, we can extract a set of bi-grams, transforming it into an unordered set for quantitative analysis. In the scope of this research, we created a wordcloud. Wordcloud is a widely-used data visualization technique in textual analysis, presenting a list of terms with varying sizes based on an associated factor.

Figure 3 shows the wordcloud of the most frequent bi-grams in the corpus of textual comments gathered from the open-ended question asking participants to provide a general comment about their online learning experience. The most frequent bi-grams are "dual mode", "positive experience", "off site", "online learning", "take exams", "study management", "great experience", "working student", "work study" and "reach university". Figure 3 indicates how students particularly appreciated online learning. Integrating the results shown in the wordcloud, and the manual reading of a sample of students' answers, we deduced a positive appreciation for the opportunity of better managing own time mainly for students that are commuters and/or workers. The overall impression is a broad appreciation and the wish to continue with remote learning.

Figure 3: Wordcloud of the most frequent bi-grams from the answers to the open ended questions to provide a general comment about the online learning experience.

5. Conclusion

Online learning represents an excellent opportunity for the educational sys-tem, and the pandemic outbreak rushed out the introduction of new technologies in educational institutions. The end of the emergency phase opens up a new phase where more attention can be paid to studying the factors influencing the success of online learning platforms to improve students' outcomes. The timing of our survey offered a great opportunity to grasp the long experience of students with online learning approaches. Nonetheless, the broad participation (18% of the total number of students enrolled at the University of Foggia) offered a great opportunity that other papers lacked.

The results of our research show how attitude towards online learning has an evident connection with personal needs of students. This is highlighted by the significant impact of being commuter or working students on their attitude: students with more time constraints due to work, or because they have to come from a city outside Foggia to attend lessons, have more positive attitudes towards online learning. Comments in the open-ended question explicitly confirms the "better time management" of online learning.

Engagement is another factor influencing student attitude. Students more engaged with professors have a more favorable attitude toward online learning. This confirms the critical role of engagement in learning, which should induce universities to try to improve the connection and the relation, preparing the teachers to create more enjoyable environments in online learning. Instead, engagement with peers is negatively related to attitude. This point leverages the primary flaw of online learning systems that, in many implementations, cannot let students establish strong relationships. Therefore, a more significant investment should be made by universities to reduce the gap between online and face-to-face in establishing engagement with peers. Although there exist different collaborative online learning environments for facing this issue, their full adoption still has a long way to go. More efforts should be put to implement environments that are more collaborative like the communities of inquiry (Fiock, 2020), designed to increase student engagement and to encourage their motivation in online courses. Already since the first decade of 2000, researchers who were studying the upcoming online learning era were also advocating that videoconferencing for holding classes was not enough, and that the future of online learning was tightly stitched with the design of new forms of learning and new ways to promote collaboration among students as it was done in face-to-face learning (Garrison and Akyol, 2012; Lambert and Fisher, 2013). In this regard, the pandemic could provide the adequate boost for the adoption of adequate solutions, such as collaborative online learning environments (Di Cerbo et al., 2008). Another flourishing field, in this sense, is that of the upcoming metaverse, where researchers are already designing immersive collaborative environments for learning purposes (Jovanović and Milosavljević, 2022).

Overall, this research has been carried out after a prolonged emergency time due to the pandemic, and the evaluation of the relation between the pandemic's emotional impact and attitude is of absolute interest. The results showed that people with a higher emotional impact also had the worst attitude toward online learning. Of course, this result has to be taken carefully; a bidirectional relation could be present between the two variables. However, this result suggests it is essential for university to take care of students' emotional situation, e.g., by offering support services. The University of Foggia was already introducing online teaching, making the transition smoother. Therefore, students widely appreciated online learning and expressed the wish to continue. This is particularly evident from the textual analysis but also from digging into other questionnaire answers. However, such a result shows that online learning is promising, but not all students have the same attitude, and several factors can influence it. This is relevant for universities to consider and continue to adapt the learning systems to fulfil the requirements and the natural attitude of all students. At the same time, they should support them in the most challenging steps. This kind of help could also change students' attitudes.

Finally, further investigation is needed to understand STEM students' worst attitude toward online learning and the reasons behind it. The limitations of this study could be helpful in guiding further research. Some of the relations are not casually explainable, and further investigation is needed. Some of the scales have been used with reduced items so to lighten the questionnaire and achieve broad participation. Future similar studies in other universities and countries could address our research findings. Lastly, we expect that more complex and explainable models could be proposed to explain students' attitude.

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